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Impact of Selected Factors on Farm Income for the Alabama Black Belt Counties and Non-Alabama Black Belt Counties

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IMPACT OF SELECTED FACTORS ON FARM INCOME FOR THE ALABAMA BLACK BELT COUNTIES AND NON-ALABAMA BLACK BELT COUNTIES

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Abstract

The study examined the impact of selected factors on farm income in the Alabama Black Belt Counties (ABBCs) and Non-Alabama Black Belt Counties (NABBCs). Data were obtained from the 2017 Census of Agriculture and analyzed using ordinary least square regression analysis. The results revealed that for the ABBCs, average size of farms, government payments, and average farm production expenses significantly affected average cash farm income (ACFI); for the NABBCs, median size of farms, government payments, and average farm production expenses significantly affected ACFI. Furthermore, for the ABBCs, average size of farms, government payments, and total farm production expenses significantly impacted net cash farm income (NCFI); for the NABBCs, median size of farms and total farm production expenses significantly impacted NCFI. The findings suggest that the average size of farms, government payments, and expenses matter in the ABBCs; and median size of farms, government payments, and expenses matter in the NABBCs.
Keywords: Alabama Black Belt Counties, Farm Expenses, Farm Income, Farm Size, and Non-Alabama Black Belt Counties

Introduction

Agricultural production is important to the U.S. economy because it contributes immensely to the GDP. It also employs many people, especially in rural areas. According to Kassel and Martin (2021), agriculture, food, and related industries in 2019, added $1.109 trillion to the GDP of the U.S. and accounted for a little over 22 million jobs in the sector. Feeding the Economy (2019) also reported that the U.S. food and agriculture sector provided about 23m in direct jobs, $783bn in direct wages; $3tr in indirect output; $885bn in business taxes, and $148bn in exports. In line with the preceding, based on the 2012 Census of Agriculture, Scott (2021) reported that California leads the country as the largest producer of agricultural products (crops and livestock), accounting for almost 11% of the national total, followed by Iowa, Texas, Nebraska, and Minnesota. These five states generated over 33% of the agricultural value of the U.S. Specifically, California had the highest value of crop sales, followed by Iowa, Illinois, Minnesota, and Nebraska. Furthermore, Texas had the highest value of livestock and related product sales, followed by Iowa, California, Nebraska, and Kansas. Relatedly, North Carolina led in value sales of poultry and eggs, followed by Georgia. Furthermore, the Farmland Information Center (2019) mentioned the importance of the economic health of agriculture within the context of farm viability and the long-term success of the sector. For example, it stated that the 2017 Census of Agriculture reported agricultural products value of $389bn compared to the $395bn obtained in 2012, down by 1.5%, which does not augur well for farm viability.

Not only is agriculture important in the U.S., but also in Alabama. Alabama is an agricultural state and agriculture has a sizeable impact on the economy. The Center for Agricultural and Rural Sustainability (2020) found that, in 2020, Alabama generated about $5bn in agricultural cash receipts. The top five agricultural commodities were broilers, chicken eggs, miscellaneous crops, cattle and calves, and cotton lint. It reported that the top five agricultural exports were broiler meat, cotton, other plant products, oilseeds and products, and livestock products. Further, it indicated that agricultural industries generated about 5% of the state's GDP. The Alabama Farmers Federation (2019a) found that food and agriculture account for 312,000 jobs in Alabama's economy. The study reiterated that, in Alabama, 13% of the jobs are in food and agriculture and 87% of the jobs are related to the agriculture downstream sector. It stated that other effects on Alabama's economy are as follows: direct wages, \$8.09bn; direct output, \$34.71bn, business taxes, \$8.33bn; exports, \$551.58mil; total wages, \$21.39bn; and total output, \$83.86bn. Yet again, the Alabama Farmers Federation (2019b) reported that agriculture has over \$70bn economic impact on the economy of Alabama. It reported that the state has over 44,000 farms, that one in nearly five jobs is linked to agriculture and forestry, and approximately 600,000 residents work either directly or indirectly in agriculture. It described the top five commodities as poultry; beef cattle; greenhouse, nursery, and sod; cotton; and soybeans. What is more, Feeding the Economy (2019) revealed that Alabama's food and agriculture provided about 330,186 in direct jobs, \$9.44bn in direct wages; \$39bn in indirect output; \$9bn in business taxes, and \$506m in exports. Additionally, Decision Innovations Solutions (2016), based on the 2012 Ag Census, communicated that agriculture and forestry make a significant contribution to the economy of Alabama as follows: \$54.9bn in sales; \$17.9bn in added value above costs, 233,793 jobs; \$1bn in state and local taxes, and \$2.3bn in federal taxes.

Since Alabama is an agricultural state, it stands to reason that all the counties have agricultural activities in them. Fundamentally, Alabama is divided into two regions, the Alabama Black Belt Counties (ABBCs) and the Non-Alabama Black Belt Counties (NABBCs). The ABBCs are those in the middle (South Central) part of the state. They run from the border of Georgia in the east to the border of Mississippi in the west. Further, farm income is critical to agricultural production. Of course, without sustainable income, practicing agriculture will be meaningless or fruitless. Yet, there have been limited studies on Alabama focusing on factors that affect farm income in the two regions. Thus, the purpose of this study was to assess the impact of selected factors on farm income for the ABBCs and NABBCs. The specific objectives were to (1) examine trends in selected factors, (2) develop models for selected factors for the regions, and (3) analyze the extent to which selected factors affect average cash farm income and net cash farm income. The rest of the article covers the relevant literature, methodology, results and discussion, and conclusion.

Literature Review

The literature review examines statistical information about the Census of Agriculture, discusses general analysis, and then follows with specific studies. For instance, the United States Department of Agriculture [USDA] NASS (2014a), based on the 2012 Ag Census, reported that there were 2.1 million farms in the U.S. This was about a 5% decrease compared to the 2.2 million farms in 2007. The average farm size in 2012 was 434 acres, compared to 418 acres in 2007, an increase of 4%; 39% of the 2.1 farms were less than 50 acres; 28% were 10-49 acres, and 11% were 1-9 acres. Further, it reported that 68% of farms were owned by full-owners; 25% were owned by part-owners, and 7% were owned by tenants.

USDA NASS (2014b), based on the 2012 Ag Census, found that agricultural sales were the highest ever, \$394.6bn; crop sales were \$212.4bn, and livestock sales were \$182.2bn. Compared to 2007, agricultural sales were $297.2bn, crop sales were $143.7bn, and livestock sales were $153.6bn.

USDA NASS (2014c), based on the 2012 Ag Census, divulged that most farms in the U.S. are small from the perspective of sales of agricultural products. For instance, 75% sold less than $50,000 in agricultural products, and 57% sold less than $10,000 in agricultural products. Additional statistics showed that less than 25% of farm household income was from farming, 61% of principal producers worked off-farm at least some days, and 40% of principal producers worked off-farm at least 200days. What is more, 46% of principal producers (main owners) had a positive net cash income from farm operations.

USDA NASS (2016), based on the 2012 Ag Census, found that 97% of farms were family-owned, and 3% were not family-owned; Of the family farms, 88% of them were small family farms with less than $350,000 in gross cash farm income. Additionally, the top five states with small farms as a percent of the total were West Virginia (97%), Tennessee (95%), New Hampshire (95%), Alabama (95%), and Oklahoma (94%).

USDA NASS (2019a), based on the 2017 Ag Census, revealed that there were about 2 million farms in the U.S. compared to about 2.1 million farms in the U.S. in 2012, a decrease of about 5%. Also, the average farm size was 441 acres compared to 434 acres in 2012 (an increase of 1.6%); 42% of the 2 million farms were less than 50 acres, 29% were 10-49 acres, and 13% were 1-9 acres. Further, it revealed that 69% of farms were owned by full-owners; 24% were owned by part-owners, and 7% were owned by tenants, not much shift compared to 2012.

USDA NASS (2019b), based on the 2017 Ag Census, reported that agricultural sales were about $389bn (compared to $395bn in 2012, a decrease of 1.5%). It also reported that the largest farms (sales equal to, or greater than $5m) comprised 1% of all farms but 35% of sales, and the smallest farms (sales equal to, or less than $50k) comprised 76% of farms but only 3% of sales. The top five states, California, Iowa, Texas, Nebraska, and Kansas had about $140bn of agricultural sales, 36% of the total sales. Farm income was about $414bn in 2017; farm expenses were $326bn in 2017, and net cash farm income was $68bn in 2017. Corresponding values for 2012 were $421bn, $329bn, and $75bn, respectively.

Regarding general analysis, Hoppe (2015) stated that larger farms are better positioned to be profitable than smaller farms; that is, farms with gross cash farm income of less than $350,000. The reason is larger farms enjoy economies of size. He further explained that smaller farms do not earn enough income from the sales of agricultural products. In fact, in some cases, cash expenses exceed cash receipts. Thus, some of these farms supplement their operations with off-farm income. The preceding notwithstanding, in certain cases, smaller farms are able to make a profit, where they get earnings above expenses.

McGinnis (2018), in his analysis on “It is Costing More to Farm”, based on farm expenses in 2017, reported that farm expenses rose from $346.9bn in 2016 to $359.8bn in 2017. Also, the average farm expenses in 2017 were $176,352, about 4% higher than the 2016 average. He reported that the four largest expenses, feed; farm services; livestock, poultry, and related products; and labor, amounted to $176.2bn, and they comprised about 49% of all the expenses.

The main farm expenses for crop farms were labor ($25.4bn), rent ($24.9bn), and farm services ($24.4bn); the main farm expense for livestock farms was feed ($53.4bn). Considering the regions, the Midwest had the most expenses ($109.1bn), followed by the Plains ($93.7bn), the West ($77.7bn), and the Atlantic ($43.1bn), and the South ($36.2bn).

USDA ERS (2021) assessed the farm income forecast for 2021. It reported that net farm income, which is a measure of profits, for 2021 was expected to be $113bn, and net cash farm income for 2021 was expected to be $134.7bn ("net cash farm income includes cash receipts from farming, as well as farm-related income, including government payments minus cash expenses. It does not include noncash items – including changes in inventories, economic depreciation, and gross imputed rental income of operator dwellings – reflected in the net farm income measure above", p. 1). Cash receipts for 2021 were expected to be $421.5bn and direct government payments in 2021 were expected to be $28bn; total production expenses were expected to be $385.5bn (nominal terms). The average net cash farm income was expected to be $93,700.

Examining specific studies, Dunn and Williams (2000) assessed farm characteristics that influence net farm income variability and losses. They used farm level, cross-section, and panel data as well as regression models, to analyze the data. They found that quantifying the effects of socioeconomic characteristics on the variability of net farm income was challenging. However, the researchers found that increases in interest costs, age, and diversification had positive relationships with income variability. Yet, only diversification had a significant effect on net income variability. Farm size also had a positive relationship with net income variability.

Poon and Weersink (2011) analyzed factors affecting variability in farm and off-farm income for Canadian producers. They used a secondary dataset of Canadian producers and assessed the data by descriptive statistics and regression analysis. They found that larger commercial producers experienced larger farm income volatility due to the fact that they are less risk-averse, or they can better handle more risk. Also, diversification and off-farm employment appear to be critical risk management strategies for such producers. Their findings also seem to suggest that government support causes some producers to adopt more risky behaviors as well as reduce self-insurance activities. They wondered if targeting government programs to specific activities could help ameliorate this situation.

Parvin and Akteruzzaman (2012) evaluated factors affecting farm and nonfarm income of Haor inhabitants of Bangladesh. They obtained data from a random sample of 60 farmers. They used descriptive statistics and regression analysis to assess whether socioeconomic factors affect farm and non-farm income. For socioeconomic factors, they reported that 80% were below 50 years; 17% had secondary education and 43% had primary school education; 50% had a household size of 1-5, and 47% had a household size of 6-10, and the average farm size was 2.2 acres. Also, they found that family size and farm size had significant and positive effects on farm income; family size had a significant and positive effect on non-farm income, and non-farm income had a significant and negative effect on farm income.

Prager et al. (2018) assessed economic returns to farming for U.S. farm households. They revealed that farm households had a mean income of $119,880. However, there were some variations in the details. First, is the mean income for households operating residential farms (that is, farms with less than $350,000 gross cash farm income, and where the primary producer has an off-farm job where he or she spends most of his or her time) was $114,703. Second, the mean income for households operating intermediate farms (that is, farms with less than $350,000 in gross cash farm income and where the primary producer has an off-farm job but spends most of his or her time on-farm), was $70,338. Third, the mean income for households operating commercial farms (that is, farms with gross cash farm income of $350,000 or more irrespective of the primary producer's job status), was $332,731. The researchers also found that, on average, farm households earned between $64,120 for intermediate farm households and $115,337 for residential farm households from off-farm activities. Furthermore, they reported that as a result of off-farm employment, many producers are able to offset farm losses with their off-farm income.

Noack and Larsen (2019) examined the contracting effects of farm size on farm incomes and food production. They used a panel dataset of rural households from Uganda and assessed the data using ordinary least squares regression. They found that output per unit of land declines with increasing farm size, but agricultural income increases with farm size. They concluded that farmers benefit from larger farms, receiving higher and more stable incomes.

Methodology

Data Source and Collection

Data were collected on several statistics for Alabama counties, for the two main regions, the Alabama Black Belt Counties (ABBCs), and the Non-Alabama Black Belt Counties (NABBCs). According to the Center for Business and Economic Research (2022), there are 17 counties in the Alabama Black Belt region. These counties are Barbour, Bullock, Butler, Choctaw, Crenshaw, Dallas, Greene, Hale, Lowndes, Macon, Marengo, Montgomery, Perry, Pike, Russell, Sumter, and Wilcox. The term "Black Belt" was originally used by Booker T. Washington to describe the dark soil in the region. However, over time, the meaning evolved to mean a county that has a higher than average percentage of Blacks. Of course, the counties not in the Alabama Black Belt region are the NABBCs. There are 50 of them, making the total number of counties in Alabama 67. The data were collected on seven factors or statistics, and they came from the USDA NASS (2017) Census of Agriculture, County Summary Highlights for Alabama. Data were obtained on the average cash farm income of the operations, the net cash farm income of the operations, the average size of farms, the median size of farms, government payments, average farm production expenses, and total farm production expenses.

Data Analysis

The data were analyzed by using descriptive statistics and ordinary least squares (OLS) regression analyses. The general model of the regression used is stated as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \ldots + \beta_j X_{ij} + \beta_j X_{ij} + \varepsilon \qquad (1)$$

Where:

Y_i is the dependent variable; β_i = coefficients; i = number of observations; j = number of independent variables; X_i = independent variables; ε = error term

Four estimation models were developed and used for the Alabama Black Belt and Non-Alabama Black Belt analyses. The estimation models 1 and 2, respectively, for the ABBCs and NBBCs, are identical, and are stated as:

$$ACFI = \beta_0 + \beta_1 ASFA + \beta_2 MSFA + \beta_3 GPAD + \beta_4 AFPE + \varepsilon \qquad (2) \ \& \ (3)$$

Where ACFI is the average cash farm income of the operations ($); ASFA is the average size of farms (acres); MSFA is the median size of farms (acres); GPAD is government payments ($1,000), and AFPE is average farm production expenses ($).

In sum, models 1 and 2 hypothesize that the average cash farm income of the operations is influenced by the average size of farms, the median size of farms, government payments, and the average farm production expenses. The general hypothesis is that the independent variables together have no effect on the dependent variable. For the specific hypothesis, it is that each individual independent variable has no effect on the dependent variable. The hypothesized signs were as follows: the average size of farms (+); the median size of farms (+); government payments (-), and the average farm production expenses (+/-). These, respectively, mean that the larger the average size of farms, the higher the average cash farm income; the larger the median size of farms, the higher the average cash farm income; the higher the government payments, the lower the average cash farm income, and the sign on average farm production expenses could go either way; it depends on the extent to which it changes. If expenses increase and receipts also go up more than expenses, then the sign will be positive. However, if expenses increase but receipts stay the same or reduce, then the sign will be negative. The details of the descriptive statistics for models 1 and 2 are shown in Appendix Tables 1 and 2.

The estimation models 3 and 4, respectively, for the ABBCs and NABBCs, are also identical, and are stated as:

$$NCFI = \beta_0 + \beta_1 ASFA + \beta_2 MSFA + \beta_3 GPAD + \beta_4 TFPE + \varepsilon \qquad (3) \ \& \ (4)$$

Where NCFI is the net cash farm income of the operations ($1,000); ASFA is the average size of farms (acres); MSFA is the median size of farms (acres); GPAD is government payments ($1,000), and TFPE is total farm production expenses ($1,000).

In brief, models 3 and 4 hypothesize that the net cash farm income of the operations is affected by the average size of farms, the median size of farms, government payments, and the total farm production expenses. The general hypothesis is that the independent variables together have no effect on the dependent variable. For the specific hypothesis, it is that each individual independent variable has no effect on the dependent variable. The hypothesized signs were as follows: the average size of farms (+); the median size of farms (+); government payments (-); and the total farm production expenses (+/-). Again, these, respectively, mean that the larger the average size of farms, the higher the net cash farm income; the larger the median size of farms, the higher the net cash farm income; the higher the government payments, the lower the net cash farm income, and the sign on total farm production expenses could go either way; it depends on the extent to which it changes. If expenses increase and receipts also increase more than expenses, then the sign will be positive. However, if expenses increase but receipts stay the same or reduce, then the sign will be negative. The details of the descriptive statistics used for Models 3 and 4 are shown in Appendix Tables 3 and 4.

The various analyses were conducted using SPSS 12.0© (MapInfo Corporation, Troy, NY). For the OLS regression analyses, the criteria used to assess the models were the adjusted R^2 ($\bar{R}^2$), R^2, the F value, t value, beta coefficients, and *p* values.

Results and Discussion

Tables 1 and 2, respectively, show trends in particular factors for the Alabama Black Belt Counties (ABBCs) and Non-Alabama Black Belt Counties (NABBCs). Specifically, the indicators are the average cash farm income of the operations, net cash farm income of the operations, average size of farms, median size of farms, government payments, average farm production expenses, and total farm production expenses. For the ABBCs (Table 1), Macon County had the lowest average cash farm income, at negative $5,086 and Crenshaw County had the highest average cash farm income, at $99,513. Again, Macon County had the lowest net cash farm income, at negative $1,897,000 and Butler County had the highest net cash farm income of the operations, at $38,843,000. Ironically, Butler County had the smallest average size of farms, at 201 acres and Wilcox County had the largest average size of farms, at 520 acres. Russell County had the smallest median size of farms, at 79 acres and Bullock County had the largest

Table 1. Trends in Factors for Alabama Black Belt Counties

Indicator	County	Lowest	County	Highest
ACFI	Macon	$(5,086)	Crenshaw	$99,513
NCFI	Macon	$(1,897,000)	Butler	$38,843,000
ASFA	Butler	201ac.	Wilcox	520ac.
MSFA	Russell	79ac.	Bullock	179ac.
GPAD	Barbour	$395,000	Pike	$3,305,000
AFPE	Barbour	$27,477	Crenshaw	$209,764
TFPE	Barbour	$5,633,000	Pike	$106,687,000

Note: ACFI is the average cash farm income of the operations; NCFI is the net cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; AFPE is the average farm production expenses; TFPE is total farm production expenses.

median size of farms, at 179 acres. Barbour County had the lowest government payments, at $395,000 and Pike County had the highest government payments, at $3,305,000. Again, Barbour County had the lowest average farm production expenses, at $27,477 and Crenshaw County had the highest average farm production expenses, at $209,764. Yet, again, Barbour County had the lowest total farm production expenses, at $5,633,000 and Pike County had the highest total farm production expenses, at $106,687,000.

For the NABBCs (Table 2), Jefferson County had the lowest average cash farm income, at negative $5,978 and Dale County had the highest average cash farm income, at $124,565. Once again, Jefferson County had the lowest net cash farm income, at negative $2,314,000 and Dekalb County had the highest net cash farm income, at $151,503,000. Marshall County had the smallest average size of farms, at 101 acres and Chambers County had the largest average size of farms, at 389 acres. Mobile County had the smallest median size of farms, at 30 acres and Fayette, Pickens, and Tallapoosa Counties had the largest median size of farms, at 105 acres each. Clarke County had the lowest government payments, at $264,000 and Houston County had the highest

Table 2. Trends in Factors for Non-Alabama Black Belt Counties

Indicator	County	Lowest	County	Highest
ACFI	Jefferson	$(5,978)	Dale	$124,565
NCFI	Jefferson	$(2,314,000)	Dekalb	$151,503,000
ASFA	Marshall	101ac.	Chambers	389ac.
MSFA	Mobile	30ac.	Fayette	105ac.
			Pickens	105ac.
			Tallapoosa	105ac.
GPAD	Clarke	$264,000	Houston	$7,557,000
AFPE	Jefferson	$19,922	Cleburne	$258,909
TFPE	Clarke	$5,013,000	Dekalb	$429,554,000

Note: ACFI is the average cash farm income of the operations; NCFI is the net cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; AFPE is the average farm production expenses; TFPE is total farm production expenses.

government payments, at $7,557,000. Jefferson County had the lowest average farm production expenses, at $19,922 and Cleburne County had the highest average farm production expenses, at $258,909. Clarke County had the lowest total farm production expenses, at $5,013,000 and Dekalb County had the highest total farm production expenses, at $429,554,000. One observation is obvious from the trends in the factors; the higher the farm expenses, the higher the farm income.

Table 3 reflects the estimates of the independent variables and their effects on the average cash farm income for the ABBCs. The F value (34.460) was statistically significant (p = 0.000). This means a strong fit between the independent variables and average cash farm income. The R^2 was 0.919 and the $\bar{R}^2$ was 0.892, implying the independent variables together explain about 90% of the variation in the average cash farm income. The t values for the average size of farms (2.296), government payments (-2.278), and average farm production expenses (10.278) were statistically significant and followed the expected signs. However, although the t value for the median size of farms (0.963) was not statistically significant, it followed the expected sign. The p values were, respectively, (p = 0.041), (p = 0.042), (p = 0.000), and (p = 0.355) for average size of farms, government payments, average farm production expenses, and median size of farms. In the case, of the average size of farms, for example, it means that as the average size of farms increases by one acre, on average, the average cash farm income increases by $82. The same reasoning applies to all the other independent variables. The findings agree with Dunn and Williams (2000), Parvin and Akteruzzaman (2012), and Noack and Larsen (2019) who reported that farm size has a positive relationship with farm income. Parvin and Akteruzzaman (2012), specifically, found that farm size had a significant and positive effect on farm income. It is not surprising that average farm production expenses have a significant effect on farm income because it has been shown by the literature that generally, higher expenses result in higher income.

Table 3. Estimates of the Independent Variables and their Effects on the Average Cash Farm Income of the Operations for the Alabama Black Belt Counties

Variable	β	t	*p*
ASFA	82.038**	2.296	0.041
MSFA	83.685	0.963	0.355
GPAD	-7.107**	-2.278	0.042
AFPE	0.603***	10.278	0.000
Constant	-53,405.712	-2.941	0.02
$F_{4,12}$	*p*	R^2	$\bar{R}^2$
34.460***	0.000	0.919	0.892

***Significant at 1%; **Significant at 5%

Table 4 shows the estimates of the independent variables and their effects on the average cash farm income of the operations for the NABBCs. The F value (161.621) was statistically significant ($p = 0.000$). This also means a strong fit between the independent variables and average cash farm income. The R^2 was 0.935 and the $\bar{R}^2$ was 0.929, again implying the independent variables together explain about 93% of the variation in average cash farm income. The t values for the median size of farms (1.690), government payments (-1.789), and average farm production expenses (21.263) were statistically significant and followed the expected signs. However, the t value for the average size of farms (-0.813) was not statistically significant, and it did not follow the expected sign. It is plausible that relatively low receipts were made in the particular year vis-à-vis the average size of farms. The *p* values were, respectively, ($p = 0.098$), ($p = 0.080$), ($p = 0.000$), and ($p = 0.420$) for median size of farms, government payments, average farm production expenses, and average size of farms. Here, using the coefficient of government payments, for instance, it means that as government payments increase by $1,000, on average, the average cash farm income decreases by $1,528. The same argument applies to the other independent variables. The findings are in agreement with Parvin and Akteruzzaman (2012), insofar as median farm size is concerned. They found that farm size has a significant and positive effect on farm income. Again, it is not surprising that average farm production expenses have a strong effect on farm income, because generally, as more expenses are incurred, there is a tendency to earn more farm income.

Table 4. Estimates of the Independent Variables and their Effects on the Average Cash Farm Income of the Operations for the Non-Alabama Black Belt Counties

Variable	β	t	*p*
ASFA	-24.593	-0.813	0.420
MSFA	132.021*	1.690	0.098
GPAD	-1.528*	-1.789	0.080
AFPE	0.500***	21.263	0.000
Constant	-17,445.079	-4.024	0.000
$F_{4,45}$	*p*	R^2	$\bar{R}^2$
161.621***	0.000	0.935	0.929

***Significant at 1%; *Significant at 10%

Table 5 presents the estimates of the independent variables and their effects on the net cash farm income of the operations for the ABBCs. The F value (61.979) was statistically significant (p = 0.000). This implies a strong fit between the independent variables and net cash farm income. The R^2 was 0.954 and the $\bar{R}^2$ was 0.938, indicating that the independent variables together explain approximately 94% of the variation in net cash farm income. The t values for the average size of farms (2.194), government payments (-3.072), and total farm production expenses (12.117) were statistically significant and followed the expected signs. In this case also, although the t value for the median size of farms (0.260) was not statistically significant, it followed the expected sign. The p values were, respectively, (p = 0.049), (p = 0.010), (p = 0.000), and (p = 0.799) for the average size of farms, government payments, total farm production expenses, and median size of farms. Using the average size of farms, as an example, it means that as the average size of farms increases by one acre, on average, the net cash farm income increases by $31,993. The same reasoning applies to all the other independent variables. The results, once

Table 5. Estimates of the Independent Variables and their Effects on the Net Cash Farm Income of the Operations for the Alabama Black Belt Counties

Variable	β	t	*p*
ASFA	31.993**	2.194	0.049
MSFA	8.465	0.260	0.799
GPAD	-4.112***	-3.072	0.010
TFPE	0.541***	12.117	0.000
Constant	-13,576.632	-2.074	0.060
$F_{4,12}$	*p*	R^2	$\bar{R}^2$
61.979***	0.000	0.954	0.938

***Significant at 1%; **Significant at 5%

again, are consistent with those of Dunn and Williams (2000), Parvin and Akteruzzaman (2012), and Noack and Larsen (2019). They found that there was a positive relationship between farm size and farm income. Indeed, as already mentioned, Parvin and Akteruzzaman (2012) found a significant effect of farm size on farm income.

Table 6 depicts the estimates of the independent variables and their effects on the net cash farm income of the operations for the NABBCs. The F value (203.972) was statistically significant (*p* = 0.000). Yet again, this implies a strong fit between the independent variables and net cash farm income. The R^2 was 0.948 and the $\bar{R}^2$ was 0.943, again indicating that the independent variables together explain approximately 94% of the variation in net cash farm income. The t values for the median size of farms (3.427) and total farm production expenses (22.270) were statistically significant and followed the expected signs. This notwithstanding, the t value for the average size of farms (-1.527) was not statistically significant and did not follow the expected sign. Additionally, the t value for government payments (-0.368) was not statistically significant but followed the expected sign. In the former case, average size of farms, it is plausible, as indicated for the ABBCs for AFCI model, Table 4, that relatively lower receipts were made in the year in question vis-à-vis the average size of farms. In the latter case, government payments, it is plausible that farmers earned relatively high receipts that year plus not too generous government payments. The *p* values were, respectively, (p = 0.001), (p = 0.000), (p = 0.134), and (p = 0.715) for median size of farms, total farm production expenses, average size of farm, and government payments. Using the coefficient of median size of farms, as an example, it means that as the median size of farms increases by one acre, on average, the net cash farm income increases by $189,596. The same argument applies to the other independent variables. In summary, insofar as farm size is concerned, specifically, the median size of farms, the results agree with what is found in the literature, for instance, Parvin and Akteruzzaman (2012) and Noack and Larsen (2019). Broadly speaking, it appears that farm size (except the average size of farms for the NABBCs for the ACFI model, Table 4, and average size of farms for the NABBCs for the NCFI model, Table 6), positively affects farm income which buttresses the point made by Hoppe (2015) who stressed that larger farms are more likely to be profitable than smaller farms.

Table 6. Estimates of the Independent Variables and their Effects on the Net Cash Farm Income of the Operations for the Non-Alabama Black Belt Counties

Variable	β	t	*p*
ASFA	-35.856	-1.527	0.134
MSFA	189.596***	3.427	0.001
GPAD	-0.256	-0.368	0.715
TFPE	0.382***	22.270	0.000
Constant	-8,967.708	-2.629	0.012

$F_{4,45}$	*p*	R^2	$\bar{R}^2$
203.972***	0.000	0.948	0.943

***Significant at 1%

Conclusion

The study assessed the impact of selected factors on farm income for the Alabama Black Belt Counties (ABBCs) and Non-Alabama Black Belt Counties (NABBCs). Specifically, it examined trends in selected factors, developed models for the selected factors for the regions, and analyzed the extent to which selected factors affect the average cash farm income of the operations and net cash farm income of the operations. The data were obtained from the USDA NASS (2017) Census of Agriculture, County Summary Highlights for Alabama and were analyzed by descriptive statistics and ordinary least squares regression analysis. The results showed that for the ABBCs, Macon County had the lowest average cash farm income and net cash farm income. Respectively, Crenshaw County and Butler County had the highest average cash farm income and net cash farm income. For the NABBCs, Jefferson County had the lowest average cash farm income, and Dale County had the highest average cash farm income. Again, Jefferson County had the lowest net cash farm income and Dekalb County had the highest net cash farm income.

The ordinary least squares regression analyses revealed that for the ABBCs for the average cash farm income model, the average size of farms, government payments, and average farm production expenses had statistically significant effects on the average cash farm income, and for the net cash farm income model, the average size of farms, government payments, and total farm production expenses had statistically significant effects on net cash farm income. Correspondingly, for the NABBCs for the average cash farm income model, the median size of farms, government payments, and average farm production expenses had statistically significant effects on average cash farm income, and for the net cash farm income model, the median size of farms and total farm production expenses had statistically significant effects on net cash farm income. The findings show that the effects on average cash farm income or net cash farm income are region-specific, probably because of the unique nature of each region. Based on the results of the study, it can be deduced that the average size of farms, government payments, and expenses (average farm production expenses and total farm production expenses) matter in the ABBCs. Moreover, the median size of farms, government payments, and expenses (average farm production expenses and total farm production expenses) matter in the NABBCs. It is recommended that efforts should be made or geared toward maintaining or increasing farmers' income in order to sustain income levels vis-à-vis expenses.

Endnotes

1. The 17 observations for the ABBCs are considered adequate because Gujarati and Porter (2009) stated that if the number of observations exceeds the number of predictor variables, then it is acceptable. Also, Pardoe et al. (2018) stated regarding sample size in the "Other Regression Pitfalls Section" that "a common rule of thumb is that 10 data observations per predictor variable are a pragmatic lower bound for sample size."
2. Histogram of Residuals (HOR) and Normality Probability Plot (NPP) were generated for all four regressions analyses (models), and in all cases, the HORs were generally in symmetry (that is, bell-shaped curves), and the NPPs were all nearly straight lines. It is assumed that no serious heteroscedasticity exists in the data.

Appendix

Table 1. Descriptive Statistics for the Alabama Black Belt Counties, Model 1, Independent Variables and ACFI

Variable	N	Min.	Max.	Mean	Std. Deviation
ACFI	17	-5,086.00	99,513.00	34,474.00	31,441.45
ASFA	17	201.00	520.00	382.88	99.42
MSFA	17	79.00	201.00	129.35	32.99
GPAD	17	275.00	3,427.00	1,811.88	911.63
AFPE	17	27,477.00	228,375.00	97,075.94	60,611.99

Note: ACFI is the average cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; AFPE is average farm production expenses.

Table 2. Descriptive Statistics for the Non-Alabama Black Belt Counties, Model 2, Independent Variables and ACFI

Variable	N	Min.	Max.	Mean	Std. Deviation
ACFI	50	-5,978.00	124,565.00	35,351.48	32,736.82
ASFA	50	98.00	389.00	197.00	69.31
MSFA	50	30.00	166.00	73.56	27.42
GPAD	50	220.00	7,557.00	2,024.72	1,747.46
AFPE	50	13,779.00	258,909.00	102,052.98	63,509.48

Note: ACFI is the average cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; AFPE is average farm production expenses.

Table 3. Descriptive Statistics for the Alabama Black Belt Counties, Model 3, Independent Variables and NCFI

Variable	N	Min.	Max.	Mean	Std. Deviation
NCFI	17	-1,897.00	54,035.00	15,080.00	15,650.03
ASFA	17	201.00	520.00	382.88	99.42
MSFA	17	79.00	201.00	129.35	32.99
GPAD	17	275.00	3,427.00	1,811.88	911.63
TFPE	17	5,633.00	113,902.00	42,063.35	34,223.04

Note: NCFI is the net cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; TFPE is total farm production expenses.

Table 4. Descriptive Statistics for the Non-Alabama Black Belt Counties, Model 4, Independent Variables and NCFI

Variable	N	Min.	Max.	Mean	Std. Deviation
NCFI	50	-2,314.00	151,503.00	24,981.64	27,706.47
ASFA	50	98.00	389.00	197.00	69.31
MSFA	50	30.00	166.00	73.56	27.42
GPAD	50	220.00	7,557.00	2,024.72	1,747.46
TFPE	50	2,963.00	429,554.00	72,207.76	70,975.37

Note: NCFI is the net cash farm income of the operations; ASFA is the average size of farms; MSFA is the median size of farms; GPAD is government payments; TFPE is total farm production expenses.

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