Agricultural Finance Review

Differences across farm typologies in capital investment during 1996-2013

Sarah Anne Stutzman,

The current issue and full text archive of this journal is available on Emerald Insight at:
www.emeraldinsight.com/0002-1466.htm

Differences across farm typologies in capital investment during 1996-2013

Sarah Anne Stutzman
Research Branch, Bureau of Economic Analysis, Washington, District of Columbia, USA

Received 3 January 2017
Revised 3 June 2017
12 July 2017
Accepted 19 July 2017

Abstract

Purpose – The purpose of this paper is to examine the impact of changes in farm economic conditions and macroeconomic trends on US farm capital expenditures between 1996 and 2013.

Design/methodology/approach – A synthetic panel is constructed from Agricultural Resource Management Survey (ARMS) data. A dynamic system GMM regression model is estimated for farms as a whole and separately within farm typology categories. The use of farm typologies allows for comparison of the relative magnitudes of these estimates across farms by farm sales level and the operator's primary occupation.

Findings – Changes in gross farm income levels, tax depreciation rates, and interest rates have a significant impact on crop farm investment, while changes in output prices, net cash farm income levels, tax depreciation rates, and farm specialization levels have significant impacts on livestock farm capital investment. The relative significance and magnitudes of these impacts differ within farm typologies. Significant differences include a greater responsiveness to change in tax policy variables for residential crop farms, greater responsiveness to changes in output prices and debt to asset ratios for intermediate livestock farms, and larger changes in commercial crop and livestock farm investment given equivalent changes in farm sales or the returns to investment.

Research limitations/implications – These findings are of interest to agricultural economists when constructing farm investment models and employing pseudo panel methods, to those in the agricultural equipment and manufacturing sector when constructing models to manage inventories and plan for production needs across regions and over time, to those involved in drafting tax policy and evaluating the potential impacts of tax changes on agricultural investment, and for those in the agricultural lending sector when designing and executing agricultural capital lending programs.

Originality/value – This study uniquely identifies differences in the level of investment and the magnitude of investment responsiveness to changes in farm economic conditions and macroeconomic trends given differences in income levels and primary operator occupation. In addition, this study is one of the few which utilizes ARMS data to study farm capital investment. Utilizing ARMS data provides a rich panel data set, covering producers across many different crop production types and regions. Finally, employing pseudo panel construction methods contributes to efforts to effectively employ cross-sectional data and dynamic models to study farm behavior across time.

Keywords Agricultural Resource Management Survey, Farm capital investment, ERS farm typologies, Farm investment, Pseudo panels

Paper type Research paper

Introduction

The period from 2000 to 2014 saw a rapid growth in farm capital investment. Total capital expenditures rose from $16.8 billion to $46.5 billion between 1996 and 2014 (Economic Research Service (ERS), n.d.b). This growth in capital expenditures resulted in 79 percent, or $107 billion, increase in the market value of the inventory of US farm equipment between 2002 and 2012 (Koenig, 2016). This rapid expansion of investment and growth of the farm capital stock coincided with rising commodity prices and farm incomes, increases in tax depreciation expense limits, falling loan interest rates, and strengthening of farm equity levels.

This paper seeks to understand the link between the growth of farm capital investment and related changes in farm economic and macroeconomic variables during this time period. It also seeks to determine differences across farms in responses to changes in variables impacting farm capital investment across farm typologies, a classification system which groups farms

0002-1466
DOI 10.1108/AFR-01-2017-0002

based on gross cash income levels and primary operator occupation. First, the definition of farm capital investment and the farm typology categories utilized in this study are introduced. Next, a dynamic panel data regression model is developed to estimate the overall impact of key variables on crop and livestock farm capital investment during this time period. This model is estimated for crop and livestock farms as a whole and within farm typologies. Finally, these results are used to motivate a discussion of the importance of and impact these differences in investment responsiveness by typology may have on future farm capital investment given changes in future prices and cash flows, tax policy, and farm debt levels.

One unique aspect of this study is the use of Agricultural Resource Management Survey (ARMS) data to study farm capital investment. ARMS is an annual survey of farms within 48 US states. The survey covers a wide range of farms producing different commodities, located in different regions, and of different economic and physical size. The majority of farm capital investment studies have utilized either aggregate time series data or farm management association data. The former does not allow us to explore the impact of individual farm level data, such as cash flows or other farm specific characteristics on investment. The latter, while correcting for this, covers only a small subset of US agricultural producers. Farms in these studies will exhibit less variety in production type and income levels compared to the US farm population as a whole[1].

A synthetic panel is created from the ARMS cross-sectional data set, utilizing mean values and pseudo panel techniques. Pseudo panel techniques allow researchers to link the behavior of farms having similar characteristics over time in cross-sectional survey data. ARMS data are currently underutilized to study many important policies, such as farm capital investment, due to the inability to track farms over time (Featherstone *et al.*, 2012). This paper contributes to efforts to further the use of ARMS data to study farm behavior over time.

Allowing for differences in elasticities across farm typologies is an additional unique aspect of this paper. While prior studies have estimated investment separately according to measures of economic size (Ariyaratne and Featherstone, 2009; Barry *et al.*, 2000; Bierlen and Featherstone, 1998; Hartarska and Mai, 2008), to the best of the author's knowledge, no other papers have used ERS farm typologies. Estimating elasticities separately by farm typology may result in more accurate estimates of the impacts on investment within groups from changes in key economic variables. This becomes important when one considers the heterogeneous distribution of farms by type and participation in farm programs[2] across farm typology categories.

The results of this study are of interest to agricultural economists, the farm manufacturing and retailing sector, the agricultural lending sector, and those involved administering the Farm Service Agency's (FSA) direct and guaranteed loan programs. Having information on the impacts of changes in key farm investment drivers by farm typology and production types allows agricultural economists to build more accurate models to forecast future farm capital investment. Obtaining additional information regarding the investment behavior of farms can assist in those in the farm equipment manufacturing and retailing sector formulate strategy, make production decisions, and coordinate demand within different regions. These estimates are useful to agricultural lenders when making current loan allocation decisions, monitoring loan health, and planning for future loan demand. Finally, these estimates can help the FSA and other government policy makers allocate funds and resources for agricultural loan programs.

Farm capital investment and farm typologies

Farm typology categories

The ARMS uses farm typologies to separate farms into categories based upon: annual Gross Cash Farm Income (GCFI), primary occupation of the operator, and family farm vs non-family farm. Farm typology categories used in this study are formed using the 2013 updated ERS farm typologies (Hoppe and MacDonald, 2013) and denoted in the ARMS data set. GCFI includes revenue from crop and livestock sales, government payments, other farm related income including custom work, machine hire, livestock grazing fees, timber sales, outdoor recreation, and production contract fees. Principle operator primary occupation classifications include farming, non-farming, or retired. The first two classifications are based upon the activity which occupies 50 percent or more of the operator's normal working hours. A farm is defined as an institution that sold, or would have sold, at least $1,000 of agricultural production during the year. Family farm is defined a farm where the majority of the business is owned by the operator and/or individuals related to the operator. Non-family farms include farms organized as cooperatives or corporations, those held in trust, and farms with a hired manager.

This study uses the three main farm typology categories: commercial, resident, and intermediate. Family farms that earned greater than $350,000 in annual GCFI and non-family farms are included in the commercial farm category. Family farms that earned less than $350,000 in GCFI are categorized as either resident or intermediate farms based upon the primary occupation of the operator. Family farms that earned less than $350,000 in GCFI and where the primary operator's occupation was farming are classified as intermediate farms. Family farms that earned less than $350,000 in annual GCFI and where the primary operator's occupation was either "other" or retired are classified as resident farms.

Table I provides information on the number and value of production of farms within each typology in 1995 compared to 2010. On average there are a fewer commercial farms compared to resident and intermediate farms, but these farms generate the majority of US agricultural output. The share of output generated by commercial farms has been increasing over time while those attributed to residential and intermediate farms have been declining. This is due to both the growth in number and increasing size of commercial farms relative to resident and intermediate farms.

Farm capital investment

In this study, farm capital investment is defined as total expenditures by a farm in a given calendar year on buildings, structures, land improvements, office equipment placed on a depreciation schedule, vehicles, tractors, farm machinery, and farm equipment less the costs of trade-ins, rebates, and discounts. Expenditures on land improvements include those to land paid by operators, landlords, and/or contractors. If applicable, these were adjusted for their portion of use in the farm business over the course of that survey year. Farmland investment and breeding livestock are not included due to different tax considerations, unavailability of data over the sample period, different lengths of investment lifespan, as well as different motivations for investment. Data for farm capital

	Number of farms (% of US total)			Value of production (% of US total)		
Typology category	1995	2010	Change	1995	2010	Change
Small farms						
Resident farms						
Retirement	16.2	16.6	0.04	1.6	1.2	−0.4
Other occupation	38.3	43.2	4.9	6.1	4.3	−2.2
Intermediate farms	38.4	28.2	−9.8	30.8	10.6	−19.8
Large farms						
Commercial farms	7.1	12.1	5	61.6	83.9	22.3

Notes: Data used in computations are from Hoppe, Robert, and James MacDonald. "Updating the ERS Farm Typology 2013", EIB-110, April 2013

Table I. Number of farms and value of production by farm typology in 1995 and 2010 investment are from the ARMS survey for years 1996-2013. Investment amounts are given in nominal dollars and were adjusted to 2012 real values using CPI data from the Bureau of Labor Statistics.

Differences in average investment levels by farm typology

Farm capital investment levels differ by farm typology, production type, and between farm typologies. This is illustrated in Figures 1-3. The average investment level is much larger for commercial farms compared to residential and intermediate farms. On average, annual

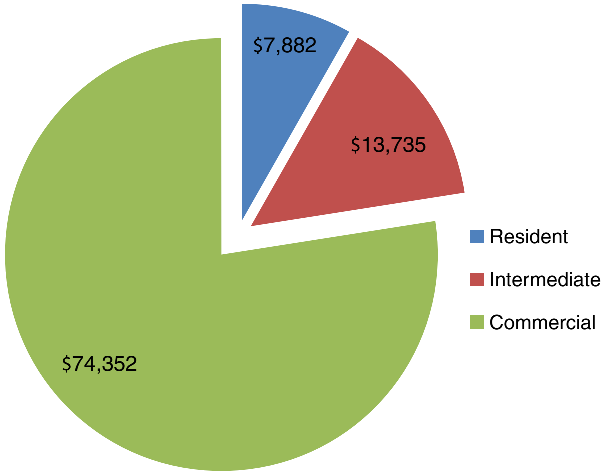


Figure 1.
Average annual investment in farm capital by farm typology between 1996 and 2013

Notes: The above are estimated using a pseudo panel dataset constructed from the ARMS cross-sectional data. Estimates obtained using the pseudo panel dataset are similar but may differ slightly from the cross sectional ARMS data estimates

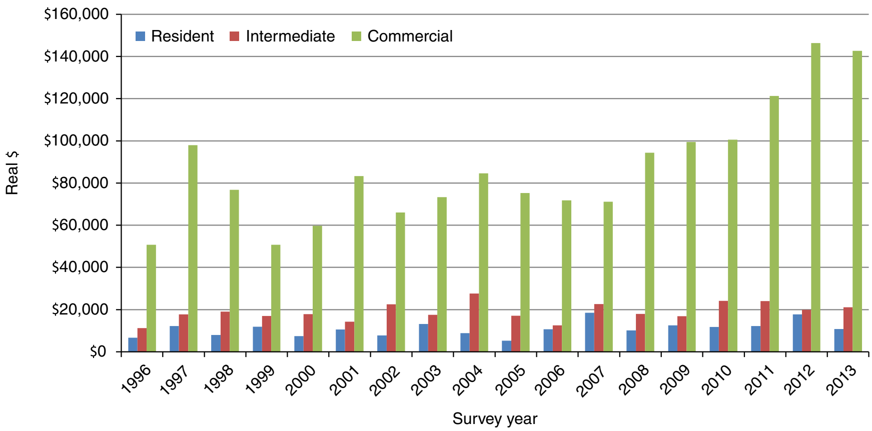
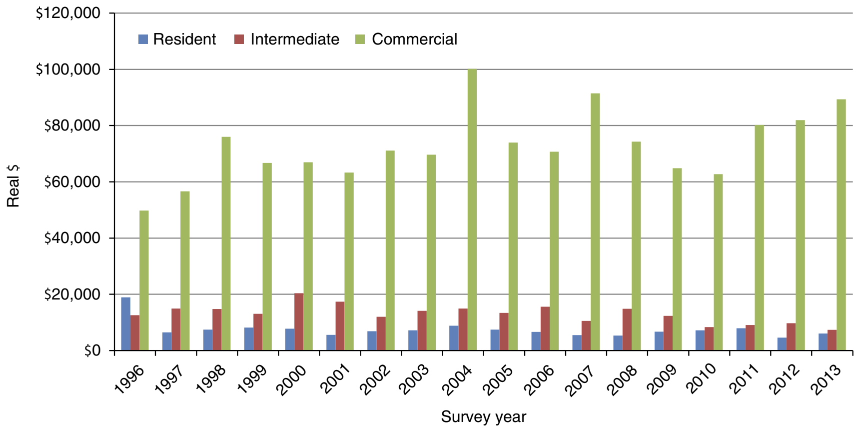


Figure 2.
Average annual crop farm investment in farm capital by farm typology between 1996 and 2013

Notes: The above are estimated using a pseudo panel dataset constructed from the ARMS cross-sectional data. Estimates obtained using the pseudo panel dataset are similar but may differ slightly from the cross-sectional ARMS data estimates



Notes: The above are estimated using a pseudo panel dataset constructed from the ARMS cross-sectional data. Estimates obtained using the pseudo panel dataset are similar but may differ slightly from the cross-sectional ARMS data estimates

Figure 3. Average annual livestock farm investment in farm capital by farm typology between 1996 and 2013

expenditures of farm capital totaled $7,882 for resident farms, $13,735 for resident farms, and $74,352 for commercial farms[3]. These differences are partially explained by the larger size, measured both in production value and in acreage, of commercial farms compared to resident and intermediate farms. As a result, commercial farm capital investment constitutes a significant portion of the total farm sector's annual capital expenditures. The average level of commercial farm capital investment rose significantly for crop farms and to a lesser degree for livestock farms between 1996 and 2013, while it remained relatively constant and/or declined for resident and intermediate farms, respectively.

Model of farm capital investment

Theoretical model

In each period, the farm operator chooses the capital stock, K_t and other inputs, X_t, to maximize the net return to an initial investment, V_0. The change in the level of capital stock between periods is governed by the equation of motion, dK/dt. The capital stock increases each period by the level of new investment, I_t, less the depreciation of the prior period stock, K_{t-1}. This can be expressed as:

$$\text{Maximize} \quad V_0 = \int_{t=0}^{L} R_t e^{-rt}$$

$$R_t = G(P_t, W_t, X_t, K_t) - C\left(\frac{dK}{dt}\right)$$

$$\frac{dK}{dt} = I_t - \varphi K_{t-1} \tag{1}$$

where r is the discount rate, L is the life of the investment, P_t and W_t are exogenous input and output prices at time t, $G(P_t, W_t, X_t, K_t)$ is a profit function, $C(dK/dt)$ is a cost function for capital, and φ is the economic rate of depreciation. By choosing a profit and cost function and solving the Hamiltonian one may obtain a numerical solution for the short-run demand for capital stock at each time period. The short-run demand for capital is equivalent to the approximate solution to the steady-state solution or the long-run profit maximizing demand for capital. This is referred to as the desired capital level and represented by K^*[4]. The desired capital level is the level farm operator would choose given no financing constraints, time lags, or other delays in adjusting the capital stock level to the new optimal level given changes in economic conditions or other factors affecting the demand for capital.

Using these relationships, one can formulate the following expression for gross investment:

$$I_t = K_t - K_{t-1} = \alpha\left[K^* - K_t\right]$$

$$NI_t = I_t - \varphi K_{t-1} \tag{2}$$

where I_t is the gross investment, NI_t the net investment, and φ the rate of economic depreciation. This is referred to as the flexible accelerator model. Gross Investment (I_t) is proportional to the difference between desired capital K^*, less capital stock levels in the prior period, K_{t-1}, times an adjustment factor, α. The adjustment factor represents the time required for the producer existing capital stock levels to their new desired levels. Net Investment (NI_t) is equivalent to gross investment less the portion of the previous capital stock that needs to be replaced due to wear or tear. The latter is represented by the rate of depreciation times the prior capital stock level (φK_{t-1}).

Reduced form model

From the flexible accelerator theoretical model a reduced form model for capital investment is formulated[5]. This can be expressed as:

$$I_t = f\left(K^*(v_t), \alpha(w_t)\right) \tag{3}$$

where investment, I_t, is a function of the level of desired capital stock, K^*, and the adjustment rate, α, and v_t are factors impacting the desired level of capital stock and w_t are factors impacting the rate of adjustment. Economic variables are chosen to represent these parameters in order to econometrically estimate the model.

Factors influencing the optimal level of capital stock include changes in output prices, expected profits, tax depreciation levels, marginal tax rates, farm size, level of output specialization, and technological change. Higher output prices and/or expected profits should generate higher returns to capital investment and provide a signal to producers to increase production levels leading to greater investment. Increases in the rate of allowable tax depreciation or the operator's marginal tax rate will reduce the after tax cost of capital, increase the return to capital, and should result in greater investment. This may occur through changes in total output and substitutions between the level of capital and other production factors, with the exact nature of this process governed by the degree of substitutability between inputs. An increase in farm size should result in higher investment, with the level of additional capital stock and new investment needed reduced by any returns to scale in the production process. The impact of output specialization on investment is governed by the return to scope between outputs and inputs. The overall impact is ambiguous. An improvement in the available technology is expected to increase the demand for new investment in this new technology, and a short run increase in investment, but may lead to a decrease in future investment especially if the newer technology leads to improved production efficiency resulting in lower overall capital needs and longer life-spans.

Factors representing changes in the adjustment rate include changes in working capital, off-farm income, and interest rates. The first two impact total cash flows and the funds available to investment in capital. Increases in the level of these variables should increase the rate of adjustment and lead to greater investment in the given period. Providing that some portion of debt financing is used in investment, a decline in interest rates will reduce the after-tax cost of capital, increase the rate of adjustment, and lead to higher investment in the given period.

Additional factors influencing the demand for farm capital investment include economy wide macroeconomic factors such as exchange rates, international trade patterns, monetary policy, the level and growth of worldwide incomes and GDP, and world-wide energy/biofuel demand and production patterns. These will impact the level of production chosen by US farmers through changes in output and input prices and global demand levels. Additional impacts will be channeled through changes in interest rates. Within my model I capture these impacts directly by including average farm loan interest rates, marginal tax rates, and tax depreciation levels. I also capture these macroeconomic impacts indirectly by including output prices and farm income.

Differences in the operator's management ability and choice of financial structure will impact levels of productivity, profitability, and resulting returns to capital. These are captured in the model by including farm income, marginal tax rates, working capital, and interest rates. These are captured indirectly via through the specification of a fixed effects model including a cohort specific fixed effects error term.

A final measure impacting capital investment decisions is the quality of the current capital stock, including such issues as idle assets, unproductivity, or obsolescence. To capture these impacts, data on the number, age, and type of the individual farm capital stock are necessary. Unfortunately, the ARMS does not collect this information. This limits the ability of this study to address the impact of asset quality on investment decisions. This downside to using the ARMS data is balanced by the incredible breadth of coverage of US farms, the identification of farm typologies, and the extent of other farm specific economic and farm household variables available in the data set.

Pseudo panels and dynamic model

Pseudo panels

The ARMS provides information on the decision of a single producer on how much to invest in that given survey year. Since different farms are sampled each year, it is difficult to determine or connect the level of investment by the same producer in prior or subsequent years. Accounting for investment choices over time is important, especially as farm capital investment is "lumpy." Purchases of capital may involve a large investment in a particular year with the expectation of utilizing the item and not making similar investments for multiple subsequent years. This results in farm investment levels exhibiting significant fluctuation between years. Constructing pseudo panels, which involves using the average level of investment of similar farms in a given year, allows us to control for this variation. Second, the level of revenues, expenses, assets, and debts often differ greatly between farms with varied producer characteristics. Utilizing pseudo panels allows us to utilize panel data models and control for these differences when performing regressions.

Deaton (1985) introduced pseudo panels as a means to construct panel data sets from balanced or unbalanced survey data sets. Subsequently, this methodology has been used in other large surveys, including the US Census and the Consumer Expenditure Survey, and to a limited extent with the ARMS (Blank *et al.*, 2004; O'Donoghue and Whitaker, 2010; Morrison-Paul *et al.*, 2004; Whitaker, 2009).

Dynamic model

A current period's investment decision may be influenced by investment decisions in prior periods due to uncoordinated life spans of most capital assets, links between financial and cash management strategies in each operating year, the amortization of debt payments spanning over multiple years, and the changing political environment leading to changes in the farm bill and other government policies. In this case, dynamic investment models may be appropriate for performing investment analysis. An additional benefit of constructing a pseudo panel from cross-sectional data is that it allows one to utilize dynamic models. Dynamic investment models allow for interactions among investment decisions today, past investment decisions, and other prior values of independent variables and heterogeneity in adjustment dynamics between different types of households or firms (Bond, 2002). Even when these adjustment factors are not the focus of study, incorporating lagged dependent variables can provide more consistent estimation of other model parameters (Bond, 2002).

Dynamic models have been used within previous agricultural economics research to explore factor demands and farm investment decisions. In this study, a lagged dependent variable is used under a system GMM estimation approach to capture investment dynamics. A similar approach of utilizing lagged variables and/or the system GMM estimator with a lagged dependent variable has been used by other studies, such as Ariyaratne and Featherstone (2009), Bokusheva *et al.* (2007), Hadrich *et al.* (2013), Hart and Lence (2004), Jensen *et al.* (1993), Micheels *et al.* (2004), and Weersink and Tauer (1989).

Methodology of constructing Pseudo panels

Forming pseudo panels involves grouping farms with similar characteristics into groups, referred to as cohorts. Cohort categories should be chosen so that the average level of key variables are similar for farms within the same group and differ across farms in different groups. Previous studies constructing pseudo panel from ARMS data used geographic region (Blank *et al.*, 2004; Morrison-Paul *et al.*, 2004; O'Donoghue and Whitaker, 2010), revenue or sales levels (Blank *et al.*, 2004; Morrison-Paul *et al.*, 2004; Whitaker, 2009), and production specialty (O'Donoghue and Whitaker, 2010; Morrison-Paul *et al.*, 2004) to form cohorts. They choose these categories because the average level of farm revenues, expenses, and assets tend to be similar for farms within these categories but differ between farms across categories.

Following the example of these past studies, cohorts are formed by splitting farms into groups based upon: commodity type, geographic region, and farm typology. The nine commodity type categories are: cash grains, tobacco and cotton, fruit, nut and vegetable, nursery and greenhouse, other crops, beef, hogs and sheep, dairy, poultry, and other livestock. These are categories assigned within the ARMS database and correspond to the commodity type, which generates at least 50 percent of the farm's annual sales. Farms that earn less than 50 percent of their sales from a specific commodity category are classified as either "other" crop or livestock. This division captures differences in production related to differences in output choices. The five geographical regions are: Western USA, Planes, Midwest, Atlantic, and Southern USA. They correspond to the NASS expenditure regions and aggregate farms based upon state in which the operation is located[6]. These regional divisions capture differences in production related to regional variation in soils, typography, weather, and other regional economic differences. The farm typology categories refer to those defined previously.

To form the pseudo panel data set, weighted mean values of the survey data set observations are calculated for farms in the same region, production type, and typology category each year. This results in a pseudo panel data set of 916 total observations over a period of 18 years. The weights are the farm expansion weights associated with the survey data and indicate the number of similar farms in the USA represented by each individual sample population. These weights are used with the survey data when computing sample estimates to obtain nationally representative statistics for US farm income and production estimates. Employing the provided ARMS expansion weights will result in estimates that account for the diversity of production type and other key characteristics of the US farm population.

Data

Data on capital expenditures and capital stock levels, tax depreciation expenses, farm acreage, output specialization, farm and off-farm income, debts, and assets are obtained from the ARMS for years 1996-2013. Revenues, expenses, and income measures represent totals earned or spent over the course of each calendar survey year. Asset, debt and net worth levels represent the dollar value as of December 31st of the given survey year. All dollar values are adjusted to 2012 real values using CPI data available from the Bureau of Labor Statistics[7].

Farm capital stock, *K*, is the dollar value of machinery, equipment, and structures at the end of the year. In keeping with the definition of farm capital investment, this does not include land or breeding livestock. Gross cash farm income, *GCFI*, includes crop and livestock sales, government payments, and other farm operating income. Net farm income, *NFI*, is measured as *GCFI* less cash and non-cash operating expenses, including depreciation, returns to labor and land, and other non-monetary expenses, and adjustments for inventory changes. Off-farm income, *OFFI,* is income earned by the farm household from non-farming activities. This includes earnings from wages, salaries and self-employment income as well as income from interest, dividends, and social security payments. Allowable tax depreciation, *DEP*, is the total tax expense taken in the given survey year for the purchase of farm capital. Working Capital, *WC*, is the difference between short-term farm assets less short-term farm debts. The Debt to asset ratio, *DTAR*, is the ratio of total farm debts to total farm assets. Farm size, *ACRES*, is the number of farm acres operated. This includes acres rented to others but not from others. Farm output specialization level, *ENTROPY*, is provided in the ARMS data. It is measured on a scale of 0 to 1, with 0 indicating that 100 percent of annual total farm sales originate from a single crop/livestock category and 1 if each crop/livestock category contributes equally to sales.

The ARMS collects data on total revenues earned and quantities sold, but not on prices received. To obtain a measure of output prices received, a price index, *PRINDEX*, was constructed using NASS data on annual national output prices received by producers within 18 commodity and livestock categories. These commodity categories correspond to those used in the ARMS survey to classify and aggregate producers into different commodity types.

Annual interest rates, *INTRATE*, are the average fourth quarter rates across ten USDA production regions for farm machinery loans from the Board of Governors Federal Reserve System Agricultural Finance Databook. Interest rates were matched with survey observations by year and production region. An average federal marginal income tax rate, *MTR*, for each farm each year was also estimated. This was done using ARMS data on total farm household income, additional survey information, and publically available IRS data. Table II provides summary statistics for the model variables within the constructed pseudo panel.

Model estimation

Empirical model estimated using pseudo panel data set

Incorporating these variables into the model in (3), normalizing by the level of farm capital[8], and choosing a linear functional form results in the following empirical model:

$$\begin{aligned} I/K_{c,t} = {} & B_0 + B_1 I/K_{c,t-1} + B_2 PrIndex_{c,t} + B_2 NFI/K_{c,t} + B_3 DEP/K_{c,t} + B_4 MTR_{c,t} \\ & + B_{10} ACRES/K_{c,t} + B_7 WC/K_{c,t} + B_8 ENTROPY_{c,t} + B_3 OFFI_{c,t} \\ & + B_5 Intrate_{c,t} + Year_t + v_{c,t}; \end{aligned}$$

$$v_{c,t} = u_c + e_{c,t} \tag{4}$$

Table II.
Pseudo panel summary statistics

Variable name	Symbol	Units	Mean	SD	Minimum	Maximum
Investment		Real $	32,583	46,086	0	684,521
Capital assets		Real $	450,193	448,428	0	7,374,659
Investment rate	*I*	Ratio	0.0624	0.0577	0	0.7432
Output price index	*PRINDEX*	Index	78.66	19.20	32.87	123.0
Return on investment	*NFI*	Ratio	0.1465	0.3137	−1.403	7.608
Tax depreciation expense rate	*DEP*	Ratio	0.0545	0.0584	0	1.243
Marginal income tax rate	*MTR*	Percent	16.55	7.00	0	39.60
Acres per unit capital	*ACRES*	Ratio	0.0016	0.0026	0	0.0331
Farm specialization	*ENTROPY*	Index	0.1256	0.0968	0	0.4703
Off-farm income	*OFFI*	Real $	63,571	52,952	−7,375	1,313,614
Working capital rate	*WC*	Ratio	0.3109	0.5438	−2.339	11.965
Interest rate	*INTRATE*	Percent	7.040	1.780	3.580	10.70
Share of building and structure investment	*SBS*	Ratio	0.0201	0.0357	0	0.6125
Share of machinery and equipment investment	*SME*	Ratio	0.0429	0.0461	0	0.7432
Gross cash farm income per unit capital	*GCFI*	Ratio	0.6972	0.8296	−0.8727	8.192
Debt to asset ratio	*DAR*	Ratio	0.213	1.640	0	68.87

where the subscript c indicates that the observation is the cohort mean, t represents the survey year, $R_{c,\ t}$ and $I_{c,\ t}$ are cohort dummies for residential and intermediate farms, Year_t is a time trend, $v_{c,\ t}$ represents the composite error term. The model states that the rate of investment today, *I/K*, is a function of the investment rate in the previous year, output prices, *PRINDEX*, returns to capital, *NFI*/K, off-farm income, *OFFI*, the rate of tax depreciation, *DEP/K,* the operator's marginal tax rate, *MTR*, the interest rate on farm loans, *INTRATE*, acres per unit capital, *Acres/K*, the level of farm output specialization, *ENTROPY*, and the working capital ratio, *WC/K*. The composite error term, $v_{c,\ t}$, is comprised of a time-invariant fixed effects error term, $u_{c,}$ representing differences in the rate of investment due to unobservable differences across cohorts, and an idiosyncratic error term, $e_{c,\ t}$. $e_{c,\ t}$ is random across cohorts and time. u_c is correlated with cohort level average differences in the independent variables and constant across time within cohorts. It reflects differences in managerial ability, geographical location, and crop or livestock output choices. Due to the correlation between u_c and the independent model variables, using OLS will result in biased estimates. To solve this issue a fixed effects model is used.

Using a fixed effects estimator for pseudo panel data was suggested by Deaton (1985) to account for cohort measurement error. Measurement error arises when constructing cohorts from cross-sectional sample data. The cohort sample means can be considered estimates of the true cohort population means. The difference between the true population estimates and the sample cohort means include differences between the population estimates and the population cohort means as well as between the population cohort means and the sample cohort means. Deaton treats the measurement error between the sample and population cohort means as a cohort fixed effect. He shows, using a fixed effect model and the between estimator, that as the number of observations per cohort approaches infinity and the number of cohorts remains fixed, the measurement error disappears and the model collapses to the fixed effects within estimator.

The most common method used to estimate a fixed effects model is the within differenced estimator. This estimator first takes the difference between periods across units, which removes the fixed effects error term, and performs the regression on these differenced results. Unfortunately, the inclusion of the lagged dependent variable results in a remaining correlation between the transformed lagged dependent variable and the transformed error term in the differenced model (Bond, 2002). To correct for this, Arellano and Bond (1991) developed a GMM estimation model. Their estimator uses an instrumental variables approach, taking first differences to remove the fixed effects, and using past values of the lagged dependent variable and the independent variables as instruments when estimating the regression in differences. Unfortunately, while this estimation method removes the bias, under certain instances the lagged levels may be week instruments for the first differences (Bond, 2002). A system GMM estimator developed by Arellano and Bover (1995) incorporates the use of lagged first differences as instruments for the levels equations into the Arellano and Bond GMM estimator. This is referred to as the system GMM estimator. It accommodates unbalanced wide data sets having many observations in a given time period relative to the number of time periods, and allows for autocorrelation between errors within cohorts over time (Bond, 2002).

Within this analysis, both the general GMM and system GMM model were tried. The system GMM model provided more consistent and robust results across typologies and hence was chosen for this analysis[9]. Robust standard errors are used to address any remaining heteroscedasticity and autocorrelation within cohorts.

The requirements for consistent estimation using the GMM system estimator are that the fixed differenced residuals are uncorrelated with the second and higher order lagged dependent variable and that the moment conditions are valid. These conditions were tested using the Arellano and Bond test for second-order serial correlation and the Hansen test for overidentifying restrictions[10]. The resulting test statistics and probability values are reported. Overall, the results of the test reject second-order autocorrelation and over-identification, supporting the appropriateness of using the system GMM model.

Separate estimation for crop vs livestock farms

The levels and patterns of investment over time differs for crop and livestock farms. This is illustrated in Figures 2 and 3. To capture these differences, the model is estimated separately for crop and livestock farms. The distinction between livestock and crop farms is based upon the commodity type category specified within the ARMS survey data and used when constructing the pseudo panel data set. Farms with a majority of revenue derived from the sale of cash grains, tobacco, cotton, fruits, nuts, vegetables, nursery, horticulture, and other crops are classified as crop farms for this study. Farms with a majority of revenue derived from the sale of beef, hogs, dairy, poultry, and other livestock are classified as livestock farms.

Separate estimation within farm typologies

Differences in the relative responses among farm typologies to changes in the model variables are next explored. While the fixed effects error term accounts for differences in the average levels of independent variables related to differences across the farm typologies, this does not address differences in the marginal responses to changes in independent variables related to farm typology differences. To examine these differences, the regressions are performed separately for each farm typology. The estimated coefficients as well as elasticities are reported and compared.

Other robustness checks

Other robustness checks performed include estimating the regression using alternative models including a basic OLS model, a random effects model, a fixed effects model using the between estimator and robust standard errors, and a maximum likelihood fixed effects model. The results were similar and are available by request.

Using the system GMM estimator, different measures of income were tested including gross cash farm income, net cash farm income, net farm income, and excluding farm income. Net cash farm income and net income measures were statistically insignificant in all regressions.

The overall results were not impacted by either excluding or including these farm income measurements. Only gross cash farm income had a statistically significant impact on farm capital investment, but also appeared to be correlated with other independent variables. The results using this measure are included in the tables for illustration, but not employed across all regressions due to this apparent multicollinearity.

Multicollinearity issues that may arise from including depreciation and marginal tax rates are verified by comparing the results of regressions including neither variable, including each variable separately, including both variables together, and specifying each variable as endogenous. The results were not significantly different in any of these instances, indicating that using both measures does not result in multicollinearity.

Given that working capital was insignificant in all regression, other measures representing different levels of credit availability and/or constraints across farms including net worth, total farm debt, farmland asset levels, farm land expenditures, and debt to asset ratios were tested. Only debt to asset ratios had a statistically significant impact on investment.

Regression results

Estimating all farm typologies in a single regression

The regression coefficients obtained by estimating the regression by grouping all farm typologies in a single regression are given in Table III for crop farms and Table IV for livestock farms. Different model formulations are presented. Model (1) is the basic regression model, model (2) replaces NFI with GCFI, model (3) excludes tax depreciation rates, model (4) replaces current tax depreciation rates with lagged tax depreciation rates, model (5) replaces working capital rates with DTAR, and model (6) with the lagged debt to asset ratio. Overall the regressions results obtained, including coefficient values and standard errors, are consistent across the various formulations.

Model	(1)	(2)	(3)	(4)	(5)	(6)
I_{t-1}	0.003 (0.023)	0.007 (0.023)	0.016 (0.024)	0.051 (0.028)	0.003 (0.023)	0.004 (0.023)
PRINDEX	0.004 (0.016)	0.004 (0.015)	−0.002 (0.016)	0.000 (0.016)	0.005 (0.016)	0.004 (0.016)
INFI	0.003 (0.007)		0.014 (0.008)	0.014 (0.008)	0.004 (0.007)	0.004 (0.007)
DEP	0.352*** (0.043)	0.168*** (0.049)			0.354*** (0.042)	0.356*** (0.042)
WC	0.002 (0.003)	−0.002 (0.003)	0.006 (0.003)	0.005 (0.003)		
MTR	9.602** (3.442)	0.746 (3.237)	14.003*** (3.543)	13.507*** (3.570)	9.674** (3.436)	9.678** (3.441)
ENTROPY	0.067* (0.029)	0.063* (0.028)	0.103*** (0.029)	0.100*** (0.030)	0.064* (0.028)	0.065* (0.028)
ACRES	73.642 (71.783)	33.315 (69.894)	219.036** (72.548)	202.232** (73.071)	76.373 (71.651)	75.742 (71.751)
INTRATE	−29.544* (13.869)	−29.420* (13.444)	−35.356* (14.444)	−36.826* (14.558)	−28.921* (13.858)	−29.344* (13.874)
OFFI	0.002 (0.003)	0.005 (0.003)	−0.001 (0.003)	0.000 (0.003)	0.002 (0.003)	0.002 (0.003)
YEAR	0.016 (0.088)	−0.000 (0.085)	0.068 (0.092)	0.048 (0.093)	0.019 (0.088)	0.019 (0.088)
GCFI		0.023*** (0.003)				
DEP_{t-1}				−12.251** (3.926)		
DTAR					0.003 (0.003)	
$DTAR_{t-1}$						−0.001 (0.003)
Constant	3.656* (1.790)	4.729** (1.737)	4.269* (1.866)	4.951** (1.889)	3.536* (1.790)	3.662* (1.792)
Number of Cohorts	1,240	1,240	1,240	1,240	1,240	1,240
RSS	61,296	57,705	66,748	67,685	61,179	61,346
Sargan	167.85 (0.1651)	176.85 (0.074)	168.24 (0.160)	177.76 (0.067)	167.96 (0.164)	168.04 (0.163)
Arellano Bond, AR(2)	−0.92 (0.353)	−0.93 (0.352)	−0.98 (0.324)	−0.92 (0.357)	−0.98 (0.326)	−0.97 (0.334)

Notes: The Dependent variable is the rate of investment. System *GMM* regression model used. Numbers in parenthesis are robust standard errors. RSS is the root sum of squares estimate. Sargan is the Sargan test of overriding restrictions where H0: the overriding restrictions are valid. χ^2 statistics are provided with probability values in parenthesis. AR(2) is the Arellano-Bond test for second order serial correlation in the first differenced residuals where H0: no autocorrelation. The *z* statistic is provided with the probability in parenthesis. *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

Table III. Crop farm regression results

Table IV.
Livestock farm regression results

Model	(1)	(2)	(3)	(4)	(5)	(6)
I_{t-1}	−0.070** (0.026)	−0.072** (0.026)	−0.060* (0.028)	−0.042 (0.031)	−0.068* (0.026)	−0.068* (0.026)
PRINDEX	0.053** (0.017)	0.051** (0.017)	0.050** (0.018)	0.052** (0.018)	0.054** (0.017)	0.053** (0.017)
INFI	0.001 (0.010)		0.003 (0.011)	0.004 (0.011)	0.007 (0.010)	0.007 (0.010)
DEP	0.228*** (0.029)	0.147*** (0.036)			0.233*** (0.029)	0.234*** (0.029)
WC	0.012* (0.006)	0.007 (0.005)	0.017** (0.006)	0.017** (0.006)		
MTR	2.538 (3.227)	0.642 (3.003)	5.086 (3.373)	4.604 (3.395)	2.612 (3.247)	2.632 (3.248)
ENTROPY	0.062** (0.022)	0.053* (0.022)	0.074** (0.023)	0.072** (0.023)	0.065** (0.022)	0.065** (0.022)
ACRES	54.677 (93.853)	−3.923 (93.741)	200.936* (97.296)	182.351 (98.146)	90.283 (93.478)	90.459 (93.482)
INTRATE	25.027 (14.343)	26.007 (14.201)	33.250* (15.036)	34.047* (15.119)	28.483* (14.345)	28.470* (14.347)
OFFI	−0.007 (0.005)	−0.004 (0.004)	−0.011* (0.005)	−0.010* (0.005)	−0.008 (0.005)	−0.008 (0.005)
YEAR	−0.256** (0.097)	−0.254** (0.096)	−0.235* (0.102)	−0.241* (0.102)	−0.231* (0.097)	−0.230* (0.097)
GCFI		0.014*** (0.004)				
DEP_{t-1}				−5.233 (3.206)		
DTAR					0.000 (0.001)	
$DTAR_{t-1}$						0.000 (0.001)
Constant	0.255 (1.871)	0.374 (1.846)	0.227 (1.966)	0.333 (1.975)	−0.152 (1.880)	−0.146 (1.879)
Number of Cohorts	944	944	944	944	944	944
RSS	38,464	37,698	42,521	42,870	38,919	38,925
Sargan	131.65 (0.870)	130.08 (0.890)	133.19 (0.848)	134.89 (0.822)	128.12 (0.912)	128.10 (0.912)
Arellano Bond, AR(2)	1.57 (0.116)	1.72 (0.084)	0.78 (0.434)	1.06 (0.288)	1.72 (0.085)	1.72 (0.086)

Notes: The Dependent variable is the rate of investment. System GMM regression model used. Numbers in parenthesis are robust standard errors. RSS is the root sum of squares estimate. Sargan is the Sargan test of overriding restrictions where H0: the overriding restrictions are valid. χ^2 statistics are provided with probability values in parenthesis. AR(2) is the Arellano-Bond test for second order serial correlation in the first differenced residuals where H0: no autocorrelation. The *z* statistic is provided with the probability in parenthesis. *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

Crop farm results

For crop farms there is a positive correlation between investment rates and tax depreciation expenses. Higher rates of tax depreciation are associated with larger tax depreciation expenses in the current period. If tax depreciation expenses in the current period are replaced with the prior period value, the opposite holds true. Higher levels of tax depreciation expenses in the prior period are associated with lower levels of farm investment in the current period. Higher marginal tax rates are associated with larger investment rates. These findings are consistent with economic theory and imply that changes in tax rates may lead to changes in farm investment behavior.

Interest rates are negative correlated with crop farm investment rates. A reduction in the average cohort level interest rate is associated with greater rates of capital investment. This is consistent with economic theory and implies that changes in farm loan terms and financing structure may lead to changes in investment behavior. The coefficients on farm size and entropy are positive but the statistical significance and size varies depending on the model formulation. While there appear to be weak links between the overall rate of total crop farm capital investment and farm size, the exact nature of these links is difficult to ascertain at this aggregated level.

There are no statistically significant impacts on investment rates for crop farms due to changes in past investment rates. It appears that, on average, past investment choices have little impact on current period investment choices for crop farms as a whole when examined at this aggregated level. There is a positive and statistically significant correlation between gross cash farm income and investment. While there is a small positive impact on investment from changes in net cash farm income and the return on investment, these are statistically insignificant for crop farms. When expenses and other non-cash items are factored into income levels, changes in income have a smaller and less uniform impact across farms on crop farm investment rates as compared to only looking at revenues.

Livestock farm results

For livestock farms, in contrast, an increase in the lagged dependent variable is negatively associated with current investment rates and an increase in the output price is positively associated with investment rates. Both of these are consistent with economic theory. One would expect that higher output prices would provide higher income levels and increase cash flow available for investment, leading to greater investment levels. Given the multi-year life span of most capital items, an increase in purchases this period will result in lower capital replacement needs in subsequent periods.

Similar to grain farms, there is a positive correlation between investment and tax depreciation rates for livestock farms. Higher levels of tax depreciation expenses are associated with greater investment in machinery in the current period. There is a positive correlation between lower levels of output specialization and the investment rate, indicating that an increase in the variety of livestock types raised may result in greater investment needs and/or rates of replacement. This would make sense as one would assume that adding a different livestock production type to the output mix would require additional investment in machinery, equipment, and structures. It also makes sense that this relationship is more apparent for livestock farms vs crop farms, indicating a lower substitutability between capital types across different livestock categories vs crop categories.

Similar to crop farms, there is no impact on the rate of investment for livestock farms from changes to the returns to investment, working capital rates, and present or lagged debt to asset ratios. Unlike crop farms, there is no statistically significant relationship between higher levels of tax depreciation in the prior period and the investment rates in the current period or between investment rates and marginal tax rates. There are small impacts on the livestock farm investment rates from changes in interest rates, farm size, and off-farm income, though these are not what one would expect and not consistent across the overall regressions.

Estimating separate regressions for each farm typology

The results obtained by performing separate regressions for each farm typology are reported in Table V crop farms and Table VI for livestock farms. These tables provide the coefficient values and standard errors for comparison with the previous results. Tables VII and VIII provide the elasticity estimates for these regressions. Model (1) uses the basic model but replaces working capital with the debt to asset ratio, model (2) replaces returns to capital with gross cash farm income, model (3) replacing debt to assets with lagged debt to assets. The regression results using the other model formulations were similar to those obtained by grouping all farm typologies into a single regression and hence are not listed in the tables.

Separate regressions by farm typology for crop farms

When regressions were estimated separately by typologies, one obtains the expected negative correlation between the rate of crop farm investment and past investment rates. The average percentage change in current investment given a one percentage change in past investment is −0.125 percent for resident farms, −0.118 percent for intermediate farms and statistically insignificant from zero for commercial farms. Higher current investment in resident and intermediate crop farms will result in lower future investment but has no discernable impact on commercial crop investment. This difference could indicate a greater tendency for resident and intermediate farms to bunch investment within specific years due to internal cash flow management, borrowing constraints, or tax considerations. Alternatively this finding could indicate that commercial farms are more likely to maintain similar rates of investment over time to replace aging machinery or to invest in new technology and have less of a need to reply on options such as substituting repairs and maintenance, short-term leasing, or other strategies to delay investment compared to resident or intermediate farms.

Table V. Crop farm results for separate regressions by farm typology

Model	(1)			(2)			(3)		
Typology	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial
I_{t-1}	−0.096** (0.034)	−0.106** (0.036)	−0.030 (0.054)	−0.092** (0.031)	−0.086** (0.033)	−0.030 (0.055)	−0.096** (0.035)	−0.094** (0.033)	−0.028 (0.045)
PRINDEX	−0.003 (0.022)	−0.011 (0.019)	0.000 (0.036)	−0.004 (0.021)	−0.010 (0.023)	−0.012 (0.033)	−0.006 (0.021)	−0.009 (0.020)	0.000 (0.027)
INFI	−0.010 (0.011)	−0.025 (0.026)	0.012 (0.015)						
DEP	0.468*** (0.138)	0.336** (0.126)	0.221* (0.086)	0.358* (0.173)	0.198 (0.128)	−0.048 (0.074)	0.473*** (0.128)	0.337*** (0.050)	0.234*** (0.059)
DTAR	0.024* (0.011)	0.018 (0.020)	0.002 (0.002)	0.020 (0.010)	0.011 (0.019)	0.001 (0.002)			
MTR	21.447** (8.182)	7.645 (4.037)	10.136 (8.199)	12.527 (8.814)	−3.669 (5.253)	−1.762 (7.092)	20.311* (8.558)	3.290 (3.530)	13.539** (4.780)
ENTROPY	0.026 (0.058)	−0.022 (0.042)	0.095 (0.095)	0.039 (0.061)	0.009 (0.049)	0.093 (0.092)	0.035 (0.057)	−0.009 (0.036)	0.096* (0.048)
ACRES	108.042 (87.479)	186.059 (134.102)	136.008 (86.769)	26.307 (86.715)	75.630 (132.638)	102.770 (71.763)	105.130 (92.823)	143.988 (129.296)	130.783 (89.727)
INTRATE	−52.914 (27.688)	−28.487 (18.074)	−26.036 (25.534)	−62.440* (26.784)	−20.428 (18.271)	−22.497 (23.885)	−56.695* (27.926)	−26.176 (20.396)	−25.022 (29.438)
OFFI	−0.020** (0.007)	0.007 (0.005)	0.004 (0.005)	−0.009 (0.008)	0.007 (0.004)	0.006 (0.004)	−0.018* (0.007)	0.007* (0.003)	0.003 (0.004)
YEAR	0.411 (0.316)	−0.158 (0.150)	0.330 (0.220)	0.418 (0.316)	−0.175 (0.156)	0.094 (0.227)	0.420 (0.312)	−0.212 (0.154)	0.375 (0.242)
GCFI				0.015 (0.009)	0.019** (0.006)	0.032*** (0.007)			
$DTAR_{t-1}$							−0.003 (0.012)	−0.008 (0.008)	0.000 (0.003)
Constant	1.895 (3.723)	8.021*** (2.080)	1.762 (4.931)	2.919 (3.752)	8.155*** (2.045)	5.485 (4.979)	2.455 (3.722)	8.714** (2.675)	0.896 (3.844)
Number of Cohorts	401	416	423	401	416	423	401	416	423
RSS	20,337	11,132	23,940	20,250	10,707	21,395	20,543	11,297	24,073
Sargan	199.14 (0.005)	174.08 (0.100)	151.98 (0.462)	196.94 (0.007)	198.20 (0.006)	160.75 (0.278)	199.92 (0.005)	178.30 (0.064)	151.14 (0.482)
Arellano Bond, AR(2)	−0.20 (0.842)	−2.02 (0.043)	−1.40 (0.163)	−0.28 (0.780)	−1.44 (0.149)	−0.81 (0.418)	−0.05 (0.961)	−1.77 (0.077)	−1.43 (0.152)

Notes: Regressions are estimated separately by farm typology. System GMM regression model used. Numbers in parenthesis are robust standard errors. RSS is the root sum of squares estimate. Sargan is the Sargan test of overriding restrictions where H0: the overriding restrictions are valid. χ^2 statistics are provided with probability values in parenthesis. AR(2) is the Arellano-Bond test for second order serial correlation in the first differenced residuals where H0: no autocorrelation. The z statistic is provided with the probability in parenthesis. *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

Table VI.
Livestock farm results for separate regressions by farm typology

Model Typology	(1) Resident	(1) Intermediate	(1) Commercial	(2) Resident	(2) Intermediate	(2) Commercial	(3) Resident	(3) Intermediate	(3) Commercial
I_{t-1}	−0.131* (0.056)	−0.135* (0.064)	−0.184*** (0.053)	−0.146** (0.053)	−0.149* (0.060)	−0.181** (0.056)	−0.136* (0.055)	−0.150** (0.049)	−0.177*** (0.041)
PRINDEX	0.028 (0.031)	0.063* (0.030)	0.093** (0.032)	0.020 (0.031)	0.064* (0.031)	0.089** (0.029)	0.024 (0.030)	0.062* (0.029)	0.096*** (0.025)
INFI	−0.016 (0.025)	0.033 (0.020)	0.014 (0.021)						
DEP	0.212** (0.073)	0.227** (0.080)	0.260** (0.090)	0.083 (0.062)	0.191* (0.090)	0.186* (0.076)	0.211** (0.073)	0.232** (0.072)	0.263*** (0.035)
DTAR	0.001* (0.001)	0.002*** (0.000)	−0.000 (0.000)	0.001 (0.001)	0.002*** (0.000)	−0.000 (0.000)			
MTR	−4.767 (7.147)	−1.700 (7.145)	4.720 (4.957)	−8.485 (7.861)	0.745 (6.468)	4.750 (4.590)	−6.894 (7.841)	1.779 (4.689)	7.209 (4.038)
ENTROPY	0.050 (0.031)	0.032 (0.039)	0.089*** (0.023)	0.030 (0.032)	0.034 (0.040)	0.077** (0.027)	0.045 (0.031)	0.037 (0.035)	0.094** (0.030)
ACRES	21.448 (157.030)	133.520 (177.421)	211.764 (131.767)	−95.497 (161.494)	101.460 (199.994)	146.689 (131.058)	7.442 (157.029)	156.594 (213.267)	233.664 (151.843)
INTRATE	38.232 (24.280)	31.055 (37.598)	11.717 (26.314)	36.873 (23.469)	31.117 (37.790)	12.953 (26.437)	36.206 (24.930)	30.436 (27.056)	13.452 (24.527)
OFFI	−0.003 (0.007)	0.001 (0.009)	−0.009 (0.006)	0.005 (0.008)	−0.000 (0.009)	−0.008 (0.005)	−0.001 (0.006)	−0.002 (0.008)	−0.011 (0.006)
YEAR	−0.262 (0.226)	−0.453** (0.151)	−0.408 (0.272)	−0.267 (0.230)	−0.465** (0.155)	−0.417 (0.275)	−0.271 (0.230)	−0.479* (0.204)	−0.395* (0.181)
GCFI				0.023* (0.012)	0.006 (0.005)	0.013* (0.005)			
$DTAR_{t-1}$							−0.000*** (0.000)	−0.002 (0.002)	0.001 (0.001)
Constant	2.189 (4.559)	1.543 (3.913)	0.188 (3.817)	2.931 (4.637)	1.471 (3.923)	0.316 (3.851)	2.959 (4.554)	1.836 (3.386)	−0.595 (3.450)
Number of Cohorts	306	316	322	306	316	322	306	316	322
RSS	12,535	12,459	10,338	11,846	12,371	10,094	12,557	12,387	10,426
Sargan	135.65 (0.810)	116.53 (0.983)	188.38 (0.021)	134.73 (0.825)	118.27 (0.977)	187.74 (0.023)	134.70 (0.825)	120.37 (0.969)	187.14
Arellano Bond, AR(2)	0.65 (0.517)	0.25 (0.803)	−0.60 (0.552)	0.37 (0.710)	0.38 (0.704)	−0.42 (0.678)	0.61 (0.541)	0.42 (0.678)	−0.63 (0.527)

Notes: Regressions are estimated separately by farm typology. System *GMM* regression model used. Numbers in parenthesis are robust standard errors. RSS is the root sum of squares estimate. Sargan is the Sargan test of overriding restrictions where H0: the overriding restrictions are valid. χ^2 statistics are provided with probability values in parenthesis. AR(2) is the Arellano-Bond test for second order serial correlation in the first differenced residuals where H0: no autocorrelation. The *z* statistic is provided with the probability in parenthesis. *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

Table VII. Crop farm elasticity estimates

Reported model	(1)			(2)			(3)		
Typology	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial
I_{t-1}	−0.125**	−0.118**	−0.022	−0.120**	−0.096*	−0.022	−0.126*	−0.111**	−0.022
PrIndex	−0.048	−0.161	0.003	−0.074	−0.140	−0.092	−0.107	−0.149	−0.001
infirealcp	−0.009	−0.040	0.047				−0.008	−0.037	0.048
DEP	0.247***	0.246**	0.215*	0.189*	0.145	−0.047	0.254***	0.252**	0.216*
DTAR	0.046*	0.034	0.006	0.039*	0.022	0.004			
MTR	0.724**	0.169	0.232	0.423	−0.081	−0.040	0.751**	0.170	0.229
ENTROPY	0.045	−0.046	0.136	0.066	0.019	0.133	0.056	−0.039	0.138
ACRES	0.025	0.059	0.042	0.006	0.024	0.032	0.027	0.058	0.042
INTRATE	−0.770*	−0.357	−0.182	−0.909*	−0.256	−0.158	−0.824*	−0.362	−0.183
OFFI	−0.378**	0.060	0.025	−0.162	0.060	0.041	−0.373**	0.060	0.025
GCFI				0.070	0.155**	0.514***			
$DTAR_{t-1}$							−0.013	−0.022	0.001
Number of Cohorts	401	416	423	401	416	423	401	416	423

Notes: *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

Table VIII.
Livestock farm elasticity estimates

Reported model		(1)			(2)			(4)	
Typology	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial	Resident	Intermediate	Commercial
I_{t-1}	−0.181*	−0.160*	−0.144***	−0.202**	−0.177*	−0.142**	−0.184*	−0.159*	−0.145***
PrIndex	0.562	1.020*	0.923**	0.404	1.038*	0.881**	0.516	1.016*	0.923**
infirealcp	−0.006	0.025	0.043				−0.006	0.025	0.043
DEP	0.151**	0.182**	0.291**	0.059	0.154*	0.209*	0.152**	0.182**	0.290**
DTAR	0.006*	0.006***	−0.002	0.005	0.006***	−0.002			
MTR	−0.188	−0.042	0.117	−0.335	0.018	0.118	−0.198	−0.041	0.121
ENTROPY	0.132	0.100	0.192***	0.079	0.107	0.165**	0.126	0.099	0.194***
ACRES	0.004	0.029	0.027	−0.016	0.022	0.019	0.004	0.028	0.027
INTRATE	0.698	0.454	0.103	0.673	0.455	0.114	0.700	0.452	0.102
OFFI	−0.072	0.011	−0.055	0.111	−0.005	−0.047	−0.070	0.011	−0.055
GCFI				0.146*	0.048	0.174*			
$DTAR_{t-1}$							−0.002***	−0.011***	0.005
Number of Cohorts	306	316	322	306	316	322	306	316	322

Notes: *,**,***Represent statistical significance at 10, 5 and 1 percent levels, respectively

There is a positive correlation between tax depreciation tax rates, marginal tax rates and the rate of investment across all crop farm typologies. The average percentage increase in the rate of investment given a one percent increase in the rate of depreciation expenses is 0.247 percent for resident farm, 0.246 for intermediate farms, and 0.214 percent for commercial farms. This rate is similar across the farm typologies, though slightly higher for resident and intermediate farms. The rate of increase in investment given a one percent increase in the average farm marginal tax rate is 0.724 percent for resident farms while it is 0.169 percent for intermediate farms and statistically insignificant for commercial farms. It is apparent that changes in the marginal tax rate have a strong impact on resident farm investment, on average, compared to the other farm typologies. These results support the idea that resident crop farm investment is extremely sensitive to changes in tax policy.

While an increase in the debt to asset ratio is positively correlated with the rate of investment on crop farms regardless of farm typology, the elasticity estimate is only statistically significant for resident farms. There finding supports a positive relationship between increases in farm debt levels and current period investment for resident farms. This could indicate that resident crop farms during this sample time period were more likely to rely on or assumed greater relative levels of additional debt to fund capital investment vs using other sources of funding. The lack of statistical significance for commercial and intermediate farms could also be indicative of lower levels of debt financing compared to other means of payment including internal cash flows, which were higher over the latter part of the sample time period due to rising commodity prices and other farm economic trends. The lagged debt to asset ratio is not statistically significant for any of the crop farm typologies, indicating no discernable impacts on the rate of capital investment in the current period given higher initial starting levels of debt. This finding appears to negative any theories of credit constraints impacting farm investment, though given the historically high income levels achieved over the course of the sample time period, one must be careful in drawing broad conclusions.

Finally, there is a negative relationship between off-farm income and investment, though this is statistically significant only for resident crop farms. This is unexpected. One would expect that higher levels of off-farm income would be correlated with more funds available for investment and hence higher investment rates. For resident livestock farms, a possible explanation may be that higher levels of off-farm income are indicative of retired operators, renting farmland to others, or hobby farms. Each of these would lead to lower investment levels and rates due to lower levels of output and/or farming intensity.

Separate regressions by farm typology for livestock farms

Similar to crop farms, livestock farm investment rates are negatively correlated with prior period investment rates, and positively correlated with tax depreciation rates and the debt to asset ratio. On average, a one percentage increase in investment last period results in a 0.181 decline in investment in resident farms, a 0.160 decline in investment on intermediate farms, and a 0.144 percent decline in investment for commercial livestock farms. While these reduction in investment more similar for livestock farms across typologies compared to crop farms, the impact is also smaller for commercial farms, indicating that commercial farms will reduce future investment rates to a lesser degree compared to resident and intermediate livestock farms given equivalent increases in current investment.

A one percent increase in tax depreciation rates is associated with a 0.151 percent increase in resident farm investment, a 0.183 percent increase in intermediate farm investment, and 0.291 percent increase in the rate of commercial farm investment. Unlike crop farms, where changes in tax depreciation rates larger impact on resident farm investment rates compared to other typologies, changes in tax depreciation rates are associated with roughly similar increases in farm investment rates across typologies, though these are slightly larger for commercial livestock farms compared to resident and intermediate livestock farms.

Unlike crop farms, there are positive and statistically significant relationships between livestock investment rates and changes in output prices as well as net farm income levels. The relationship between investment rates and output prices is statistically significant for intermediate and commercial livestock farms and statistically significant for the return on capital for intermediate farms. Changes in output prices result in larger changes in livestock investment rates compared to changes in income levels. A one percent increase in an index of output prices results in a 1.020 percent increase in the rate of investment for intermediate farms, and a 0.923 percent increase in the rate of investment for commercial farms. In contrast, a one percent increase in gross cash farm incomes is associated with a 0.146 percent increase in the rate of investment for resident farms, and a 0.174 percent increase in the rate of investment for commercial farms. Changes in the rate of return lead to even smaller increases in livestock investment rates than do changes in output prices or revenues. A one percent increase in the rate of return is associated with an additional 0.025 percent increase in investment for intermediate livestock farms.

Similar to crop farms, there is a positive relationship between the debt to asset ratio and investment rates. This is significantly different from zero for resident and intermediate farms only. Unsurprising, higher levels of investment are associated with the assumption of debt in the current period for resident and intermediate livestock farms. Unlike for crop farms, there is a statistically significant negative relationship between the lagged debt to asset ratio and livestock farm investment rates. A one percent increase in the initial debt to asset ratio at the beginning of the period is associated with a 0.002 and 0.011 percent decrease in the rate of investment for intermediate and resident farms. This supports the theory that smaller farms with higher initial levels of debt may be credit constrained, resulting in lower borrowing ability and investment rates in the current period. In contrast, there is a positive relationship between the prior debt to asset ratio and the rate of investment for commercial livestock farms. A one percent increase in the initial debt to asset ratio results in a 0.005 percent increase in the rate of investment in the current period. This finding could be indicative of greater levels of debt used to fund investment activities over time on large commercial livestock farms during this sample time period, though more research would need to be done to verify this conclusion.

Further discussion

Farm prices, income levels, and commercial farm investment

The model estimates indicate that commercial crop farm investment is highly sensitive to changes in gross cash farm income and livestock farm investment to changes in output prices, gross cash farm income and the returns to investment. Since commercial farms comprise a majority of annual farm capital expenditures, this means that farm sector investment rates will be highly sensitive to changes in price and/or incomes. This has been reflected in the impact that declining farm incomes have had on farm equipment sales and the financial health of the farm equipment manufacturing and retailing sector over the post 2014 time period. Between 2014 and 2015, farm gross cash incomes fell 11 percent and net incomes fell 20 percent (ERS, n.d.b). During the same time period the Equipment Manufacturing Association (EMA) estimated that sales of 40 to 100 hp tractors fell 16.2 percent and sales of 100-HP tractors fell 34.5 percent in December 2015 compared to December 2014 (Wiesemeyer and Bernard, 2016). The fall in investment demand has spill over impacts on overall US economic output and employment levels. In response to lower sales, Deere & Co. has had to lay off employees at several plants and reduce its total full-time workforce (Bloomberg News, 2016). Moving forward, agricultural manufacturing and retailing firms will benefit from strategies such as costs cutting, mergers and acquisitions, diversification to non-agricultural manufacturing markets and making greater use of detailed data on investment demand by farm type to more accurately forecast future investment demand.

Tax policy and residential farm investment

Given the majority of farm household taxes are computed based upon total farm household income (Williamson, 2013), farm capital investment which reduces net farm income levels may also reduce total household taxable income levels. Changes in tax policy to have a strong impact on the "character, amount and timing of their [capital asset's] acquisition or sale" (Williamson, 2013). The strength of these impacts is seen most markedly in the relative size of the residential crop farm tax depreciation and marginal tax rate elasticity estimates. In addition to their direct impact on investment, changes in tax policy and other legislation will have indirect impacts on other farm decisions, including farmland purchases, non-farm asset purchases by farm households, participation in farmland conservation measures, and farm dissolution and succession decisions. These impacts, in turn, will have subsequent impacts on farm capital investment decisions and the overall health of the farm economy sector. As a result, current and future discussions regarding altering federal tax policy must consider the impact of such changes on farm capital investment.

Working capital levels, debt levels, and intermediate farm investment

This model indicates that current intermediate farms investment rates and debt to asset levels are positively correlated. While, on average the model is unable to discern statistically significant impacts on investment from changes in working capital levels, this does not rule out large impacts from falling working capital levels on farms within specific categories. Working capital levels can vary tremendously across farms. Averages can mask important differences in the level of individual farm debts, assets, and working capital. One such difference is that certain farms use debt more aggressively. Patrick *et al.* (2016) found that while overall debt levels in 2016 were low, 11 percent of farms specializing in crop production and 9 percent of those engaged in livestock production had debt to asset ratios in the critical zone (greater than 40). In addition, the time period of this study reflected a period of high crop incomes. Declines in income can have very different impacts on farms, especially small scale farms.

One way in which the farm sector has sought to support capital investment is through direct and indirect loan programs. These can provide a way to mitigate short-term gaps between cash flows and investment needs a well as support the capital investment needs of beginning farmers and ranchers. Unfortunately, a less robust farm economy increases the demand for and stretches the resources and funding of these programs. The strong link between intermediate farm investment rates and debt levels found in this study further supports the need to ensure that these programs have adequate funding and support moving forward.

Summary and conclusion

This study estimates a dynamic model of US farm capital investment using a synthetic panel constructed from the ARMS data set. This synthetic data set incorporates detailed farm level observations for producers in 48 US states over the 1996-2013 time period. Differences in investment rate responses given changes in agricultural microeconomic factors and economy wide macroeconomic factors are explored by investment type and across farm typologies.

Changes in gross cash farm income, current and lagged depreciation tax rates, and interest rates result in statistically significant changes in crop farm investment rates.

Livestock farm investment rates, on average, are impacted by changes in output prices, gross cash farm income levels, tax depreciation rates, and farm specialization levels. Within the different typologies one finds larger investment rate responses given equal changes in tax depreciation rates, marginal tax rates, interest rates and off-farm income for resident crop farms. Changes in output prices and debt to asset ratios generate larger relative changes in intermediate livestock farm investment rates. Larger crop and livestock commercial farm investment rates changes are correlated with equivalent changes in gross cash farm income and the returns to investment levels. Increases in past investment rates are found to reduce investment rates in the current period for all typologies, with the exception of commercial crop farms.

These findings have important implications for the agricultural machinery and equipment production and retail sector, federal tax policy, and the farm lending sector. These results and future studies utilizing ARMS data and pseudo panel methods can provide valuable insights to assist individuals and businesses in each of these areas anticipate and plan for future agricultural capital investment needs. The ability of the farming sector to maintain adequate farm capital investment levels has long-term impacts on the ability of the USA to feed growing populations at home and abroad, allow farms to expend to serve new domestic and international markets, to reduce the environmental footprint of farming through technology adoption, and to support and expand the US manufacturing and equipment sector. These in turn will have long-term impacts on the health of both the agricultural sector and the greater US economy.

Notes

1. See Kuethe *et al.* (2014) for additional information on the differences between ARMS data and Farm Management Association data sets.
2. For further information on differences in farm type distributions and participation in farm programs by typology see Hoppe and Banker (2014).
3. The above are estimated using the pseudo panel data set constructed from the ARMS cross-sectional data. Estimates obtained using the pseudo panel data set are similar but may differ slightly from the ARMS cross-sectional data estimates.
4. For additional details solving for $K_t^*(P_t, W_t)$, see Weersink and Tauer (1989).
5. Additional benefits of using the reduced form approach include: not having to specify a specific functional form for profits or costs, being able to incorporate factors affecting investment beyond the prices and quantities of outputs and inputs, and the ability to represent adjustment costs by including lagged independent variables. See Jensen *et al.* (1993) and Weersink and Tauer (1989) for additional justification.
6. For more information on and a map of the NASS production regions see "Charts and Graphs: ARMS II Farm Production Regions Map", available at: www.nass.usda.gov/Charts_and_Maps/Farm_Production_Expenditures/reg_map_c.php
7. For more information on the ARMS survey data and collection procedures, see ERS (n.d.a).
8. This follows the example of other farm investment studies, including Ariyaratne and Featherstone (2009) and Barry *et al.* (2000). Normalizing key model variables by the level of farm capital, $K_{i,t}$ reduces the level of heteroskedasticity that would be otherwise caused by differences in revenue and expense levels between farms related to differences in farm sales.
9. For more information on the estimation procedure, see Stata documentation for stdpdsys found at www.stata.com/manuals13/xtxtdpdsys.pdf.
10. For more information on these tests see Stata Documentation "xtdpdsys postestimation" at www.stata.com/manuals13/xtxtdpdsyspostestimation.pdf#xtxtdpdsyspostestimation.

References

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies*, Vol. 58 No. 2, pp. 277-297.

Arellano, M. and Bover, O. (1995), "Another look at the instrumental variable estimation of error-components models", *Journal of Econometrics*, Vol. 68 No. 1, pp. 29-51.

Ariyaratne, C.B. and Featherstone, A.M. (2009), "Impact of government payments, depreciation and inflation on investment behavior in American agriculture sector using sample of Kansas farms", paper presented at the AAEA & ACCI Joint Annual Meeting, Milwaukee, WI, July 26-29, available at: http://ageconsearch.umn..edu/bitstream/20374/1/sp04mi01pdf (accessed April 1, 1996).

Barry, P.J., Bierlen, R.W. and Sotomayor, N.L. (2000), "Financial structure of farm businesses under imperfect capital markets", *American Journal of Agricultural Economics*, Vol. 82 No. 4, pp. 920-933.

Bierlen, R.W. and Featherstone, A.M. (1998), "Fundamental Q, cash flow, and investment: evidence from farm panel data", *The Review of Economics and Statistics*, Vol. 80 No. 3, pp. 427-435.

Blank, S.C., Erickson, K.W., Moss, C.B. and Nehring, R. (2004), "Agricultural profits and farm household wealth", *American Journal of Agricultural Economics*, Vol. 86 No. 5, pp. 1299-1307.

Bloomberg News (2016), "Farm boom fizzles as US crop surplus expands financial strain", Farm Web, January 17, available at: www.agweb.com/article/farm-boom-fizzles-as-us-crop-surplus-expands-financial-strain-naa-bloomberg/

Bokusheva, R., Valentinov, V. and Anpilogova, V. (2007), "The investment behavior of Russian farms", *Post-Communist Economies*, Vol. 19 No. 1, pp. 53-71.

Bond, S.R. (2002), "Dynamic panel data models: a guide to micro data methods and practice", *Portuguese Economic Journal*, Vol. 1 No. 2, pp. 141-162.

Deaton, A. (1985), "Panel data from time series of cross-sections", *Journal of Econometrics*, Vol. 30 No. 1, pp. 109-126.

Economic Research Service (ERS) (n.d.a), "ARMS farm financial and crop production practices", available at: www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation.aspx (accessed April 1, 2016).

Economic Research Service (ERS) (n.d.b), "Farm income and wealth statistics", available at: www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/ (accessed May 25, 2017).

Featherstone, A.M., Park, T.A. and Weber, J.G. (2012), "Keeping ARMS relevant: extracting additional information from ARMS", *Agricultural Finance Review*, Vol. 72 No. 2, pp. 233-246.

Hadrich, C.J., Larsen, R. and Olson, F.E. (2013), "Impact of the section 179 tax deduction on machinery investment", *Agricultural Finance Review*, Vol. 73 No. 3, pp. 458-468.

Hart, C.E. and Lence, S.E. (2004), "Financial constraints and farm investment: a Bayesian examination", *Journal of Business & Economic Statistics*, Vol. 22 No. 1, pp. 51-63.

Hartarska, V. and Mai, C. (2008), "Financing constraints and the family farm: how do families react?", paper presented at the Southern Agricultural Economics Association Annual Meeting, Dallas, TX, February 2-6, available at: https://core.ac.uk/download/pdf/6530941.pdf (accessed April 1, 2016).

Hoppe, R.A. and Banker, D.E. (2014), "Structure and finances of US farms: family farm report, 2014 edition", Economic Information Bulletin No. EIB-132, US Department of Agriculture, Economic Research Service, available at: www.ers.usda.gov/webdocs/publications/43913/50364_eib-132.pdf?v=42103 (accessed May 27, 2017).

Hoppe, R.A. and MacDonald, J.M. (2013), "Updating the ERS farm typology", US Department of Agriculture, Economic Research Service, Economic Information Bulletin No. EIB-110, available at: www.ers.usda.gov/webdocs/publications/43742/36482_eib110.pdf?v=41368 (accessed May 27, 2017).

Jensen, F.E., Lawson, J.S. and Langemeier, L.N. (1993), "Agricultural investment and internal cash flow variables", *Review of Agricultural Economics*, Vol. 15 No. 2, pp. 295-306.

Koenig, S. (2016), "Economic report: update on US farm equipment trends", Office of Regulatory Policy, Farm Credit Administration, March 22, available at: www.fca.gov/Download/EconomicReports/7%20UpdateOnFarmEquipmentTrends.pdf (accessed May 25, 2017).

Kuethe, T.H., Briggeman, B., Paulson, N.D. and Katchova, A.L. (2014), "A comparison of data collected through farm management associations and the agricultural resource management survey", *Agricultural Finance Review*, Vol. 74 No. 4, pp. 492-500.

Micheels, E.T., Katchova, A.L. and Barry, P. (2004), "Machinery investment in Illinois: a study examining existing investment motivations", paper presented at AAEA Annual Meeting, Denver, CO, July 1-4, available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.506.2986&rep=rep1&type=pdf (accessed May 27, 2017).

Morrison-Paul, C.J., Nehring, R. and Banker, D. (2004), "Productivity, economies, and efficiency in U.S. agriculture: a look at contracts", *American Journal of Agricultural Economics*, Vol. 86 No. 5, pp. 1308-1314.

O'Donoghue, E.J. and Whitaker, J.B. (2010), "Do direct payments distort producers' decisions? An examination of the farm security and rural investment act of 2002", *Applied Economic Perspectives and Policy*, Vol. 32 No. 1, pp. 170-193.

Patrick, K., Kuhns, R. and Borchers, A. (2016), "Recent trends in US farm income, wealth, and financial health", *Choices*, Vol. 31 No. 1, pp. 1-8.

Weersink, A.J. and Tauer, L.W. (1989), "Comparative analysis of investment models for New York dairy farms", *American Journal of Agricultural Economics*, Vol. 71 No. 1, pp. 136-146.

Whitaker, J.B. (2009), "The varying impacts of agricultural support programs on US farm household consumption", *American Journal of Agricultural Economics*, Vol. 91 No. 3, pp. 569-580.

Wiesemeyer, J. and Bernard, R. (2016), "AEM tractor, equipment sales results latest sign of Ag financial struggles", *Pro Farmer*, January 25, available at: www.profarmer.com/article/aem-tractor-equipment-sales-results-latest-sign-of-ag-financial-struggles-naa-jim-wiesemeyer–roger-bernard/

Williamson, J.M. (2013), "Agriculture, the tax code, and potential tax reform", *Choices*, Vol. 28 No. 2, pp. 1-5.

Further reading

Benjamin, C. and Phimister, E. (2002), "Does capital market structure affect farm investment? A comparison using French and British farm-level panel data", *American Journal of Agricultural Economics*, Vol. 84 No. 4, pp. 1115-1129.

Internal Revenue Service (IRS) (1996-2013), Tax publications for years 1996-2013, available at: www.irs.gov/Forms-&-Pubs

Corresponding author
Sarah Anne Stutzman can be contacted at: sarah.stutzman@bea.gov