Graduate School Form
30 Updated 12/26/2015

PURDUE UNIVERSITY
GRADUATE SCHOOL
Thesis/Dissertation Acceptance

This is to certify that the thesis/dissertation prepared

By Sarah Stutzman

Entitled

U.S. Farm Capital Investment 1996-2013: Differences by Farm Size and Operator Primary Occupation

For the degree of Doctor of Philosophy

Is approved by the final examining committee:

Dr. Timothy Baker
Chair

Dr. Michael Langemeier

Dr. John McConnell

Dr. Jennifer Ifft

To the best of my knowledge and as understood by the student in the Thesis/Dissertation Agreement, Publication Delay, and Certification Disclaimer (Graduate School Form 32), this thesis/dissertation adheres to the provisions of Purdue University's "Policy of Integrity in Research" and the use of copyright material.

Approved by Major Professor(s): Dr. Timothy Baker

Approved by: Dr. Gerald Shively 4/25/2016

Head of the Departmental Graduate Program Date

U.S. FARM CAPITAL INVESTMENT 1996-2013: DIFFERENCES BY FARM SIZE AND OPERATOR PRIMARY OCCUPATION

A Dissertation

Submitted to the Faculty

of

Purdue University

by

Sarah Stutzman

In Partial Fulfillment of the

Requirements for the Degree

of

Doctor of Philosophy

May 2016

Purdue University

West Lafayette, Indiana

ACKNOWLEDGEMENTS

I would like to acknowledge the assistance and support of my advisor, Timothy Baker, and my committee members: Michael Langemeier, Jenny Ifft, and John McConnell. I would also like to acknowledge the support of the Agricultural Economics Department at Purdue and in particular the department head, Dr. Ken Foster, the graduate coordinator, Dr. Gerald Shively, as well as the guidance and moral support of Dr. Michael Wetzstein. Access to the ARMS data and support in working with the data can be accredited to Farm Economy Branch of the Economic Research Service, USDA. In particular I would like to acknowledge the assistance of Mitch Morehart in first bringing me to ERS and showing me how to work with the ARMS data, Ron Durst in compiling the tax information, Jim Williamson for guidance in working with the data and econometrics assistance, Bob Dubman in providing data assistance, Todd Hubbs in working through structuring the model, and everyone else who provided feedback when I presented my ideas both in the Fall of 2014 and the Spring of 2016.

TABLE OF CONTENTS

Page

Page

Page

Page

LIST OF TABLES

Table Page

Table Page

LIST OF FIGURES

Figure Page

Figure Page

ABSTRACT

Stutzman, Sarah A. Ph.D., Purdue University, May 2016. U.S. Farm Capital Investment 1996-2013: Differences by Farm Size and Operator Primary Occupation. . Major Professor: Timothy Baker.

This study analyzes U.S. farm level investment in machinery, equipment and structures between 1996-2013. A synthetic panel is constructed using annual cross-sectional farm level observations from the Agricultural Resource Management Survey (ARMS). Cohorts are formed by grouping farms into similar categories based upon farm production type, region and farm typology. This methodology allows the use of fixed effects to control for cohort specific and time-invariant similarities in investment levels, addresses non-investment in a single period by using cohort average investment rates, and allows links between investment levels and other key determinants across cohorts over time.

Within farm typologies, farms are classified based on levels of gross cash farm income (GCFI) and operator primary occupation. Commercial farms have GCFI greater or equal to \$350,000. Resident farms have GCFI less than \$350,000 and a primary operator occupation other than farming. Intermediate farms also have GCFI less than \$350,000 but identify their primary occupation as farming. Making these distinctions is important if investment behavior is related both to GCFI levels and primary occupation.

Previous studies find differences between in farm capital investment rates and changes in sales or income measurements, tax policy variables, and cash flow measurements based on farm size and levels of off-farm income. To test if these same relationships hold when using the ARMS data and farm typology categories, I develop three hypotheses based upon these three commonly found and/or asserted relationships. The three hypothesis developed are that

compared to the other farm typologies there is a greater increase in investment rates given: 1) an increase in output prices and returns on investment for commercial farms, 2) changes in tax policy variables for resident farms, and 3) changes in measures of credit constraints for intermediate farms. I test these hypotheses by allowing these key coefficients to vary across farm typologies. Given the results of these tests, I find evidence to support the first two hypotheses, though this varies by commodity type, but little evidence to support the third.

Using the estimated model, changes in specific model coefficients are used to explain differences in investment levels in 2013 vs. 1996 and to estimate average farm investment levels in 2024. Changes in farm capital investment in 1996 vs. 2013 can be attributed to changes in output prices, interest rates and year specific impacts. Decreases in net farm incomes on commercial grain and livestock farms, declining output prices for intermediate livestock farms, lower bonus tax depreciation expense limits on resident livestock farms, and rising interest rates for grain farms across typologies lead to large declines in average farm investment in 2024 compared to 2013.

CHAPTER 1: INTRODUCTION

Investment in machinery, equipment and structures by farms in the U.S. grew rapidly over the past two decades. In 1996, U.S. farms, on average, spent $19.6 billion on long-lived machinery, equipment and structures (excluding dwellings). By 2013 annual farm capital investment rose to $37.9 billion (USDA, August 2015). This rise in investment coincided with favorable economic conditions in agriculture, including rising commodity prices and resulting growing farm incomes, generous tax investment incentives, low interest rates, rising farm equity and decreasing debt levels. These favorable conditions are not expected to continue. After declining in 2014, net cash receipts and net cash farm income are expected to again decrease by 9% and 21% respectively (USDA, November 2015). Short and long term farm debt has seen a steady rise over the past year and is expected to have grown by 3.5% in 2015 (USDA, November 2015). While future equipment and machinery tax deduction levels are set to continue at their current levels for the immediate future (Gearhardt, January 2015), loan interest rates are expected to increase in response to the Federal Reserve's increase in the federal funds rate in December of 2015 with further planned in 2016. Given the different and interconnected impacts of changes in each of these on farm capital investment and the capital intensive nature of US agriculture production, those engaged the manufacturing and retailing of farm capital as well as policy makers involved in agricultural loan programs would benefit from obtaining accurate estimates of the potential impacts of said changes on future levels of farm capital investment.

An obstacle to obtaining such estimates is that there are few studies examining how investment responds to changes in key drivers of investment which differentiate between farms based upon farm typology, a classification of farms based on Gross Cash Farm Income levels and the primary occupation of the principle operator. I believe that average farm capital investment responds differently to changes in key determinants of investment given differences in farm typologies. Estimated investment responses need to reflect this. Not accounting for these differences, and instead using the average across farms, may mask important fundamental differences between how farms will respond given changes in the key drivers of investment.

These differences are important considering the heterogeneity in U.S. farm capital investment levels across farms of different sizes. The US agricultural sector is comprised of small segment of large commercial farms, earning large farm incomes and making large annual capital investments, and many smaller farms accounting for a much smaller portion of total farm capital investment. Examining the investment behavior of large commercial farms as well as smaller farms, and differentiating according to operator occupation, has value. Given that they comprise a greater portion of total production and investment, the behavior of large commercial farms will have a greater impact on total agricultural capital investment in the economy, as well as on the technology employed and environmental impact associated with producing the US food supply. Alternatively, many beginning and disadvantaged farmers do not fall into the large commercial farm category, but instead operate farms with lower farm income levels and/or may have another primary off-farm occupation. Determining what drives investment on smaller farms is a key priority when planning for and evaluating programs to ensure that beginning and/or part-time farm operators have the needed capital and technology to earn a reasonable profit, and the opportunity to grow, if they desire.

In this study, I will examine differences in investment levels in response to changes in key drivers of investment across farm typologies. The structure of the paper is as follows: I define farm typologies, examine capital investment levels by farm typology, and review the literature. Next, I develop a fixed effects regression model, explain the methodology for constructing pseudo panels from ARMS survey data, and introduce the three hypothesis I will test using this model. These hypotheses are that investment rates will increase more on A) commercial farms given changes in output rates and/or returns to investment, B) resident farms given changes in tax policy, and C) intermediate farms given changes in liquidity or other measures of credit and financial constraints. After estimating the model separately for farms within the following three categories[1]: 1) grains, 2) fruit, nut, vegetable, and nursery crops (FNV), and 3) livestock farms, I compare my results to other panel data farm capital investment studies and test my hypothesis. Next, I use the estimated model elasticities to calculate the

[1] Commodity type is defined as earning at least 50% of Gross Cash Farm Sales from the commodities within these categories.

change in average farm capital investment levels between 1996 and 2013 attributed to changes in model variables between these years. Finally, I estimate projected changes in average farm capital investment in 2024 compared to 2013 given projected changes in key model variable.

Previous studies have examined the impact of credit constraints on farms according to asset levels (Ariayante and Featherstone, 2009), age (Ariayante and Featherstone, 2009; Barry et al., 2000; Bierlen and Featherstone, 1998) and measures of credit worthiness (Barry et al., 2000). They have not differentiated between the impacts of output prices, returns, liquidity levels, and taxes on farms accounting for differences in primary operator occupation. My study is different from others in that I split farms into categories based upon levels of net farm income as well as primary operator occupation and look for differences in investment responses given changes in taxes, liquidity levels, output prices, return, and other measures of financial constraints.

Another distinguishing factor is my use of ARMS, a national survey of U.S. farms. Other farm level panel data studies have used a relatively small set of farms within a limited geographical region. In contrast, I utilize survey data from farms within 48 different U.S. states. By employing the provided weights, I am able to obtain estimates representative of the US farm population as well as to distinguish between farms using the detailed production and financial farm business and household level data within the survey. Finally, to account for links between investment levels over multiple time periods I construct a synthetic panel using ARMS observations. This approach has not been utilized to study investment behavior within the ARMS survey in any currently published literature.

Research on investment responses to changes in economic conditions which adequately accounts for differences by farm size, operator occupation, and production type can provide useful information on future farm capital investment demand. Having more detailed information on commercial farm capital investment demand in particular can assist the farm manufacturing and retail sector control production levels and coordinate to meet demand within differing regions and commodity specific capital good sectors. Having accurate information regarding future farm capital demand can also assist FSA program administrators in the planning and implication of FSA operating loan programs. Farm loan programs have target participation rates for beginning or socially disadvantaged farmers and ranchers, and limited resource farms. Farms meeting these criteria, on average, have smaller than average levels of farm income and/or a primary occupation other than farming. The knowledge generate in this study will be helpful in meeting these goals. Finally, many of the key determinants of farm investment are also affected by changes in farm policy, farm programs, and general economy-wide macroeconomic policy. This includes farm income levels and variability, commodity prices, tax rates and interest rates. Knowing the impacts of changes in investment given changes in these variables will be helpful for those involved in decision making within these diverse areas.

CHAPTER 2: BACKGROUND AND INVESTMENT BY FARM TYPOLOGIES

In this chapter I describe the ARMS data from which I draw information on farm capital investment and other farm characteristics, explain the farm typology classification system and details regarding the characteristics of farms within each typology, provide an outline of what is included when I speak of farm capital investment, and provide some information of the different levels of investment across farm typologies, regions, and production category types.

2.1 Arms

The data on investment and distribution of farms by typology is from the USDA Agricultural Resource Management Survey (ARMS). ARMS is a national survey jointly conducted by the USDA and NASS. Sampled farms[2] from within 48 states are asked to provide information on farm production processes, financial measurements for the given survey year, and farm operation and household characteristics. The ARMS is unique in that it is the only national survey to provide such a detailed level of information on farm household income and characteristics on such a large scale (National Research Council, 2008). The information collected is vital to the role of the fulfilling the USDA's mandate to prepare estimates of U.S. farm income and production practices (National Research Council, 2008).

ARMS follows an annual, multiphase, multi-frame, stratified, probability sampling design (ERS, ARMS Farm Financial and Crop Production Practices, 2014). The survey is conducted in three phases. Phase one occurs in the spring of the survey year and consists of verifying the farm fits the criteria of the survey in a given year. The phase two occurs in fall and obtains information regarding farm production practices. Phase three occurs in the winter following the

[2] According to the USDA definition, a farm refers to a place with the potential of producing $1,000 or more worth of agricultural commodities a year (MacDonald et. al, 2013)

survey year. In phase three detailed information regarding revenue and expense data are collected.

The list of farms to sample are chosen from within two frames, the list frame and the area frame. The list frame is a list of farms maintained by NASS and updated at a regular basis using different sources. The area frame comes from the NASS June area survey and is obtained by determining farms that appear on the June area survey with those not on the list frame. This attempts to cover any farms missing on the list frame so that all farms are sampled accordingly.

There are multiple versions of the survey corresponding to different survey phases and methods of delivery. Versions 2-4 correspond to phase two. These commodity specific phase two surveys are conducted by personal interview. Versions 1 and 5 correspond to phase three. Version 1 of the phase three survey is conducted by personal interview. The data from this version is referred to as the Cost and Returns report (CRR). Version 5 refers to a separate mail-in version of the phase three survey. This is called the Core version and contains less questions compared to version 1. Within this study I only use observations from the CRR.

ARMS is a stratified sample. This stratified procedure reflects the expected differences in farms given farm size, location and production type. Farms are grouped in stratum based upon the farm's state, gross sales, and commodity type. Farms are randomly sampled from within stratum. Stratified sampling relies on the theory that by grouping farms into samples and sampling within these smaller units, more efficient estimates, with lower sample variances, can be made as compared to random sampling within the whole population (Dubman, 2000). In addition, this reduces the cost of sampling while ensuring that the population in question is adequately covered.

Each farm observation has a weight reflecting the probability that they are selected out of the general population. These weights are used to calculate population statistics and when making population inferences. These help insure that estimates for the farm population drawn from the sample results correctly reflect national farm averages. The weights adjust for nonresponse to both individual questions and to the survey as a whole. I take advantage of the weights[3] provided and employ these when estimating population means and when constructing

[3] There are different weights provided depending on the versions of the survey used. Within this study I use the weights associated with the CRR when calculating summary statistics for the population and when forming the pseudo panel datasets. These weights were revised in 2012 to reflect 2012 Census of

my pseudo panels. This allows my results to correctly reflect the U.S. Farm population over time rather than just the choice of farms sampled that year.

The ARMS survey data provides a cross sectional sample of farms where the individual farms and the number of farms sampled differ each year. The ARMS survey began in 1996. Since its inception, the number of surveyed farms has grown. Within this study, I use years 1996-2013. This provides 152,609 initial observations across 18 years. Table 1 lists the number of observations within the survey dataset by year.

Table 1: Number of Farms by Year in ARMS Constructed Dataset

Year	Number of Farm Observations
1996	6,985
1997	9,024
1998	7,991
1999	9,778
2000	7,712
2001	5,439
2002	9,949
2003	6,048
2004	6,706
2005	6,828
2006	6,456
2007	6,179
2008	6,149
2009	6,575
2010	6,775
2011	9,488
2012	18,728
2013	15,799
Total	152,609

2.2 Farm Typologies

Farms are grouped by typologies to further explore differences in investment behavior. Below I provide a description of the typologies as well as characteristics of farms within each typology.

Agriculture data on farm numbers and revisions of acreage and production statistics by NASS (USDA, 2016). The weights employed in this study reflect this revision.

2.2.1 Defining Farm Typologies

I separate the farm observations into categories based upon level of annual Gross Cash Farm Income (GCFI) and the primary occupation of the operator. These categories are based upon the 2013 updated ERS farm typologies (Hoppe and MacDonald, 2013). Using average measurements across farms of different size and types can mask significant levels of variation and be misleading (Hoppe, 2014). To account for this variation, ERS has developed a set of farm typologies, or classifications. These typologies classify farms into homogenous groupings. These groupings allow for more accurate estimates of average levels of farm revenues, incomes, production expenses, assets, debts, and other key farm and operator characteristics.

The first division is between family farms and nonfamily farms. Family farms are any farm where the majority of the business is owned by the operator and/or individuals related to the operator. Nonfamily farms include those organized as cooperatives or nonfamily corporations, those held in trust, and farms with a hired manager. Family farms are further divided into small and large family farms[4]. Small family farms are defined as having GCFI of less than $350,000. Small family farms are further split into resident and intermediate farms. Intermediate farms are small family farms where the primary operator identifies their primary occupation as farming. Resident farms are small family farms in which the primary operator lists a primary occupation other than farming. This includes retired farm operators and those employed in a non-farming primary occupation. Commercial farms, are farms with an annual GCFI of greater than $350,000. This category makes no distinction between the primary operator's occupation and includes nonfamily farms. These farm typology categories are summarized in Table 2 below.

---

[4] Under the ERS farm typologies small family farms include 1) retirement farms, where the primary occupation is retirement and GCFI < $350,000, 2) off-farm occupation farms, where the primary occupation is nonfarm and GCFI < 350,000, 3) low-sales, with farming as the primary occupation and GCFI < $150,000, and 4) moderate sales, where farming is primary occupation and GCFI between $150,000 and $350,000. Commercial farms include the ERS farm typologies 1) mid-sized family farms, with GCFI between $350,000 and 999,999, 2) large family farms, with GCFI between $1,000,000 and $4,999,999, 3) very family large farms, with GCFI of $5,000,000 or more, and 4) non-family farms. Using the ERS conventions, I combine retirement farms and off-farm occupation farms in the resident farm category and low-sales and moderate sales in the intermediate farm category. I combine mid-sized family farms, large family farms, very large family farms and nonfamily farms to form the commercial farm category.

Table 2: Summary of Farm Typologies

Resident	Intermediate	Commercial
•Annual Gross Cash Farm Income[1] <$350,000 •Primary occupation[2] other than farming	•Annual Cash Farm Income <$350,000 •Primary occupation farming	•Annual Gross Cash Farm Income ≥ $350,000

[1] Gross Cash Farm Income 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 (Hoppe, 2014).
[2] Occupation is the task for which the operator spends 50% or more of his or her work time

The GCFI threshold for the farm typology definitions are not adjusted for yearly changes in GCFI due to inflation. It is acknowledged that not adjusting the thresholds over time may result in a small number of farms moving between categories due to changes in inflation rather than due to any change in the actual production level (Hoppe and McDonald, 2013). Small farms earning near the $350,000 GCFI threshold within the early years of our sample time period are the most likely to move to the commercial farm category given inflation over time. The impacts of this is an area deserving of future study.

2.2.2 Distribution of Farms within Typologies over Time

Table 3: Number of farms and value of production by farm typology in 1995 and 2010

Typology Category	Number of Farms (% of US total)			Value of Production (% of US total)		
	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	+5.0	61.6	83.9	+22.3

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

Table 3 lists the percentage of farms within each typology by number and value of production. The majority of US farms are small farms. In 2010, 87.1% of all US farms were small family farms, while only 12.1% were classified as large commercial farms. Over the past two decades the number of resident farms in the U.S. has increased, while the number of intermediate farms has declined. There are many reasons for this change. The increase in the number of retirement resident farms can be associated with an overall increase in the median U.S. farm operator age. Hoppe and MacDonald (2013) link this increase in the median farm operator age with improved health care and advances in farm equipment. Technology changes have also facilitated part-time farming, allowing more acres to be operated in less time and leaving more time for off-time employment (MacDonald et al., 2014). Additional reasons for the expansion in the number of residential farms may include the desire to combine a rural lifestyle with some level of crop or livestock production (MacDonald et al., 2014) and increasing off-farm employment opportunities in rural areas.

The majority of US farm production is produced by large commercial farms. In 2010, large family farms produced 83.9% of all US agricultural value of production. Over the last two decades, a larger share of US production has moved to larger farms (Hoppe and MacDonald, 2013). This is due to both increases in the total number of and average size of commercial farms. Increases in the average size of commercial farms has been driven by producers taking advantage of economies of scale in the production of specific agricultural commodities (MacDonald and McBride, 2009; MacDonald and Newton, 2014) as well as advances in technology and capital inputs, allowing a single operator to farm more land in less time (MacDonald et al., 2013).

2.2.3 Distribution of Farms within Typologies by Production Type

Small farms dominate production within a few specific commodities. While only comprising 26% of the value of production in 2011, they comprised 56.4% of poultry value of production, 51.1% of hay value of production, and 47.7% of other livestock value of production, including horse, sheep and goats. They are 32% of beef calf farms and a significant presence within the category of other field crops[5] (Hoppe, 2014). Within commodities dominated by large farms, such as cash grains and dairy production, small farms have been able to find niches in high value production segments requiring relatively low capital investment and lower labor inputs. This includes local food hubs and farmers markets, the production of artisian cheese and other dairy products, and the breeding of high value calves (Vogel and Low, 2015; MacDonald and Newton, 2015).

In contrast, cash grain, dairy and hog farms are dominated by larger commercial farms, where larger capital costs and initial investment levels create barriers to entry. Large farms, while comprising 60% of US farm production make up 60% of cash grain, 66% of hog, 76% of high-value crop, 70% of dairy, and 82% of cotton value of production (Hoppe, 2014).

2.2.4 Distribution of Farms within Typologies by Region

The above differences in farm size by commodity specialization are related to differences in the distribution of farm typologies across US regions. Figure 1 provides a map of the ERS Production Regions and Table 4 provides the average number of farms by farm typology type within each Production Region over the 1996-2013 time period.

[5] This includes conservation reserve acres. A significant portion of the acreage under conservation reserve plans are owned by resident farms

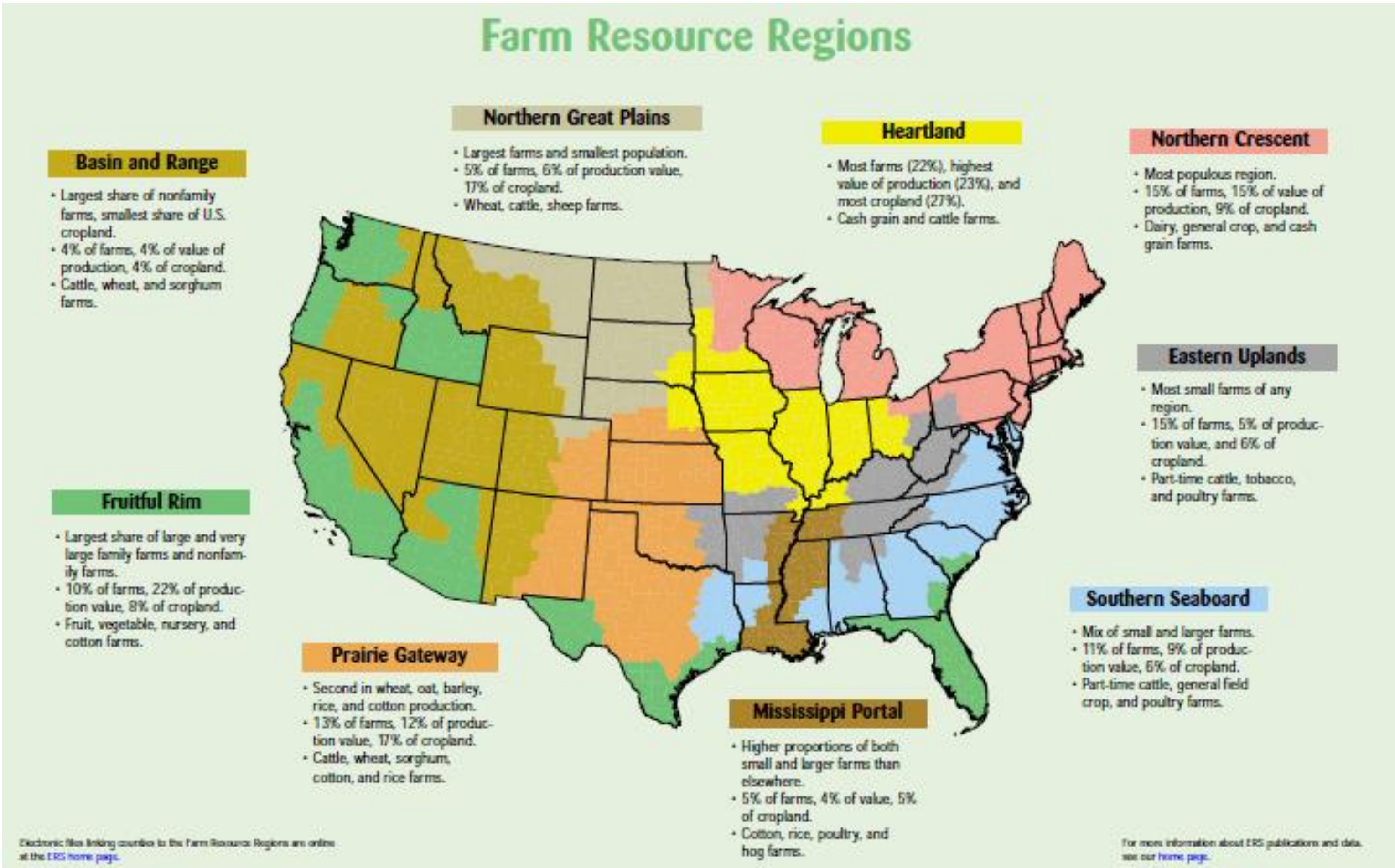

Figure 1: Map of ERS Farm Resource Regions

Table 4: Percentage of Farms within each Farm Typology by ERS Farm Resource Region over the Period of 1996-2013

	Farm Typology		
Farm Resource Region	Resident	Intermediate	Commercial
Heartland	69%	24%	8%
Northern Crescent	69%	27%	4%
Northern Great Plains	45%	43%	12%
Prairie Gateway	66%	30%	4%
Eastern Uplands	72%	26%	2%
Southern Seaboard	74%	19%	7%
Fruitful Rim	68%	24%	9%
Basin and Range	67%	29%	5%
Mississippi Portal	72%	22%	6%

ARMS data used. Sample observations are weighted by their percentage of the US farm population

Resident farms form a larger share of farms in the East Coast and interior Southeast regions. Intermediate farms form a large share of farms in the interior sections of the US. The largest share of commercial farms is located in the Northern Plains, the Heartland, and Western and Southern Seaboard regions, corresponding to areas of cattle, cash grain, fruit, nut and vegetable production.

2.3 Investment

In the next section I provide details on my measurement of investment as well as a summary of the different investment patterns by farm typology.

2.3.1 Defining Investment

Farm Capital Investment in this study is the sum of expenditures by a farm in a given calendar year on buildings, structures, improvements, office equipment placed on a depreciation schedule, vehicles, tractors, farm machinery, and farm equipment less the costs of trade-ins, rebates and discounts. If applicable, these were adjusted for their portion of use in the farm business over the course of that survey year. Improvement include improvements to structures as well as to land. The expenditures on buildings and land improvements include those paid by operators as well as by landlords and contractors.

2.3.2 Treatment of Farmland

Farmland investment is not included in the measure of farm capital investment. Data on farmland purchases within ARMS is only available 2004 onward. Very few producers in the ARMS survey made an investment in farmland in a given survey year compared to investments in other capital items. Table *5* gives the average percent of farms within the ARMS survey between 1996-2013 making expenditures on different types of capital items.

Table 5: Average Percent of Farms[1] Making an Expenditure within a Given Survey Year in Farm Capital over the Period 1996-2013[2] by Farm Typology and Capital Investment Type

Item	Farm Typology		
	Resident Farms	Intermediate Farms	Commercial Farms
Equipment, Machinery	32%	40%	66%
Buildings and Improvements	23%	25%	39%
Farmland[2]	1%	2%	6%
Breeding Livestock	13%	21%	23%

[1]Sample observations are weighted by their percentage of the US farm population
[2]Farmland investment data is only available in ARMS starting in 2004. As a result, farmland investment is the average of observations using survey years 2004-2013.

Only 1% and 2% of resident farms and 6% of commercial farms made a farmland purchase in a given year. This is in contrast to 32% of resident farms, 40% of intermediate farms and 66% of commercial farms making a purchase in machinery and equipment, and 23% of resident farms, 25% of intermediate farms, and 39% of commercial farms investing in buildings, structures or improvements.

Another reason why farmland is excluded from investment is that the decision to invest in farmland is different from that of capital, machinery, equipment and livestock. There are different economic and tax depreciation characteristics and motivations for purchasing farmland compared to machinery and equipment. Farmland is subject to potential capital gains taxes at the time of sale. Capital gains seldom apply to machinery or equipment sales. Farmland has a longer expected lifespan. Farmland is expected to last over an infinite horizon while the value of machinery, equipment and buildings decline over their useful life. This results in different methods of valuing farmland and discount rates over time. The market for farmland is thin, with the amount of farmland that is sold in a given year is small in comparison to total available farmland. This results in greater price fluctuations in farmland values compared to machinery, equipment and structures.

While I do not include farmland within my measure of farm capital investment, I do acknowledge that farmland purchases can impact the level of non-farmland capital stock purchased. Investment in farmland can either reduce funds available for investment in other assets such as building, machinery and equipment. On the other hand, farmland purchases leading to an increase in total farmland operated should increase the need for additional capital stock and thus lead to additional non-farmland capital stock. To control for the later, I include a measure of farm acres operated. To account for the impact of farmland purchases on total investment funds, I try including both the level of farmland assets, the purchase amount of farmland assets, and a dummy variable representing if the farm purchased farmland or not. These are explained further in section 6.10.

2.3.3 Treatment of Breeding Livestock

Investment does not include investment in breeding livestock unless specifically stated and only in that instance for farms specializing in livestock production. Table A4 gives the average percent of farms in the ARMS by typology and livestock production type investing in breeding livestock over the period 1996-2013.

Table 6: Average Percentage of Farms[1] Making an Expenditure within a Given Survey Year in Breeding Livestock during the Period of 1996-2013 by Livestock Production Category

Livestock Category	Farm Typology		
	Resident Farms	Intermediate Farms	Commercial Farms
Beef Cattle	22%	32%	52%
Dairy	21%	38%	39%
Hogs	30%	39%	20%
Poultry	7%	15%	18%
Other	5%	9%	14%

[1]Sample observations are weighted by their percentage of the US farm population

Over the past two decades, breeding livestock was a significant investment for producers specializing in beef cattle and dairy product production. While, on average, only 13% of resident farms, 21% of intermediate farms, and 23% of commercial farms made an investment in breeding livestock in a given year, 32% of intermediate and 52% of commercial beef farms and 32% of intermediate and 39% of commercial dairy farms made breeding livestock investments. Livestock investment exhibits tax characteristics common to farmland, such as capital gains realized at the point of sale, but like machinery, equipment and structures has a finite life span.

When investment in breeding livestock is included, it only covers expenditures for purchased breeding livestock and not livestock raised for breeding purposes. Breeding livestock asset values includes the value of both purchased and raised breeding livestock. This could create measurement issues when calculating the rate of breeding livestock investment. This may be most problematic for small farms, for which livestock raised for breeding purposes may constitute a large portion of farm investment. Accounting for the costs of raised breeding livestock will be pursued in further work but is beyond the scope of this study currently without access to the base survey data.

2.4 Investment by Farm Typology

Commercial farms are more likely to invest in a given year and, on average, make larger annual investments compared to resident and intermediate farms.   Over the period of 1996-2013, 43% of resident farms, 54% of intermediate farms, and 79% of resident farms made an investment in machinery, equipment or structures. Given a farm choose to make an investment in the given survey year, the average investment was $15,013 for resident farms, $22,849 for commercial farms and $100,165 for commercial farms.

2.4.1 Differences Across Farm Typologies Over Time

The average annual level of farm capital investment on U.S. farms rose tremendously from 1996 to 2013. The majority of this rise in investment has been driven by commercial farms. Figure 2 shows the percentage of farms making an investment by farm typology each year over the period of 1996-2013.

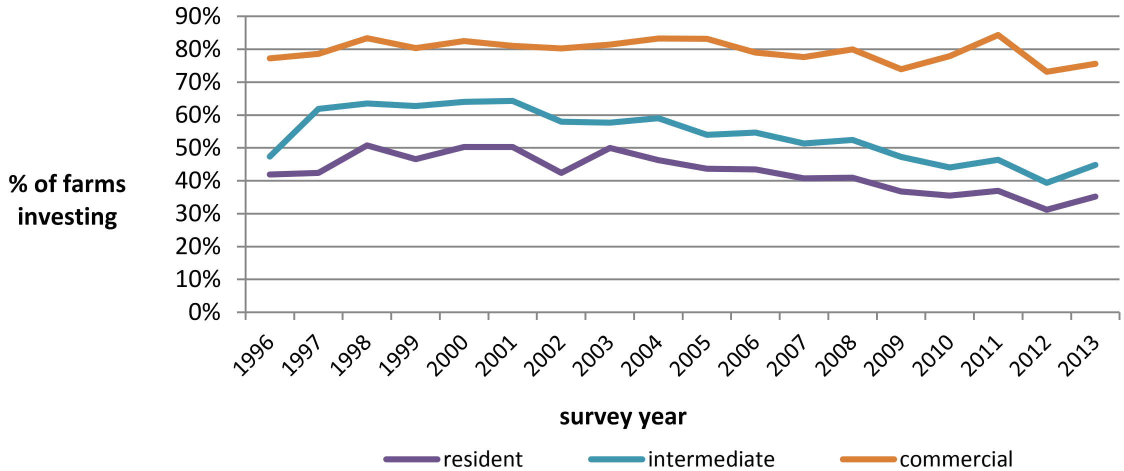

Figure 2: Percent of Farms[6] Making an Expenditure on Machinery, Equipment, and Structures by Year and Farm Typology using ARMS Data over the Period 1996-2013

The percentage of commercial farms making an investment each year was larger and remained relatively constant compared to the portion of resident and intermediate farms making investments. In contrast, the percentage of resident and intermediate farms making an investment increased in the beginning of the sample period and then declined over the latter time period. The percentage of small and resident farms making capital purchases exhibited a greater level of variability over time period as well. The variability of investment was 5.7% for resident farms, 7.6% for intermediate farms, and 3.2% for commercial farms.

There are also differences in the trends between farm typologies regarding the average level of farm capital investment. This is illustrated in Figure 3 below.

[6] Sample observations are weighted by their percentage of the US farm population

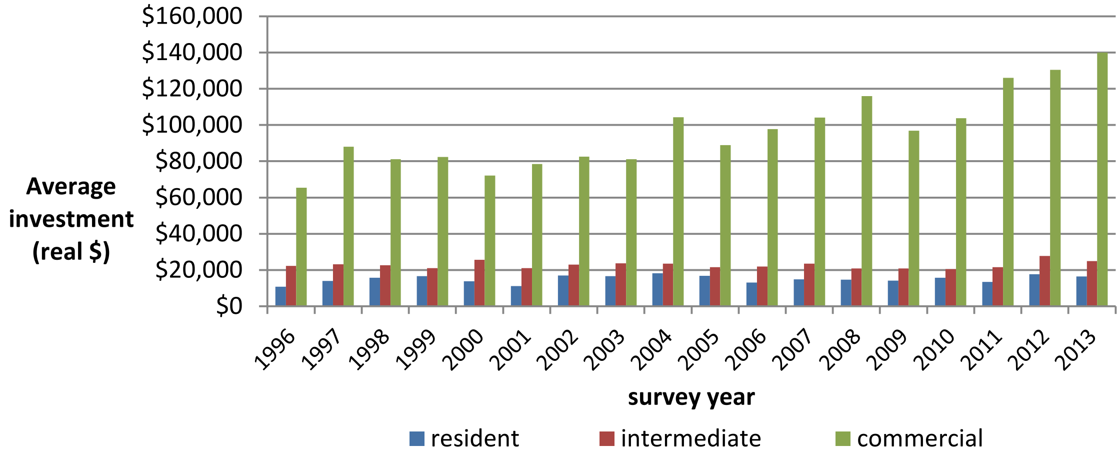

Figure 3: Average[7] Expenditures on Machinery, Buildings, and Structures over the Period of 1996-2013 by Year and Farm Typology

There is a clear upward trend in the average level of investment on commercial farms between this time period, resulting in the average annual level of investment doubling on commercial farms by the end of 2013 compared to 1996. The average annual level of investment on resident and intermediate farms increased but to a much smaller degree in comparison to that of commercial farms. The variability of the level of investment between years was also greater for commercial farms compared to resident and intermediate farms. The variance between years of investment was $2,047 for resident farms, $1,852 for intermediate farms, and $20,202 for commercial farms.

2.4.2 Differences Across Farm Typologies by Region

Figure 4 provides the average annual investment level by farm typology and ERS production region.

[7] Sample observations are weighted by their percentage of the US farm population

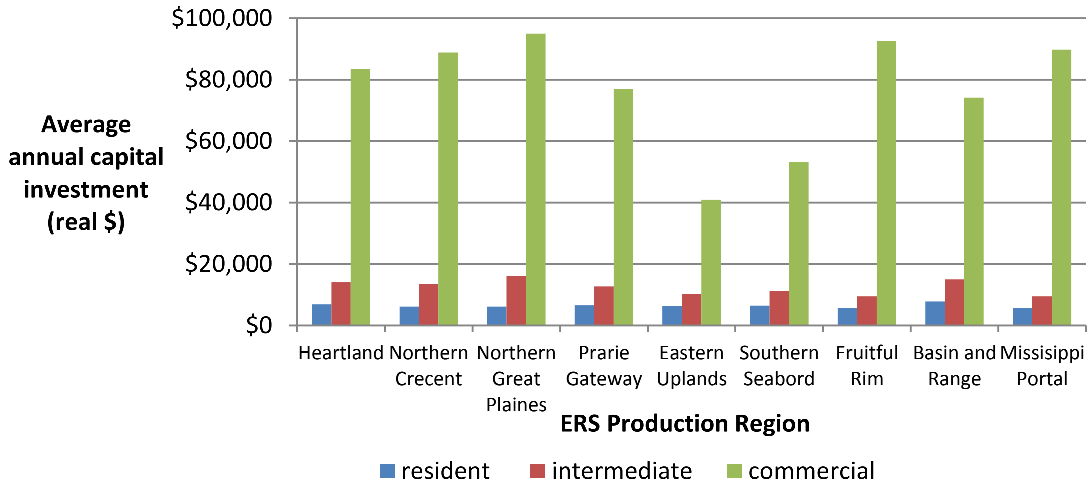

Figure 4: Average[8] Expenditure on Machinery, Equipment and Structures within a Given Survey Year over the Period 1996-2013 by Region[9] and Farm Typology

Investment was larger, on average, in the Northern and the Fruitful Rim regions of the US, where the main commodities produced include wheat, corn, soybean, cattle and dairy, are production is dominated by large farms. In contrast, investment was lower in regions dominated by resident farms, such as the Eastern Uplands and Southern Seaboard regions. There was a greater variance in the level of investment between commercial farms across different regions compared to resident and intermediate farms.

2.4.3 Differences Across Farm Typologies by Production Type

Figure 5 shows the average annual investment level by farm typology and commodity type.

[8] Sample observations are weighted by their percentage of the US farm population

[9] See Figure 1 for a map and descriptions of the ERS Production Regions

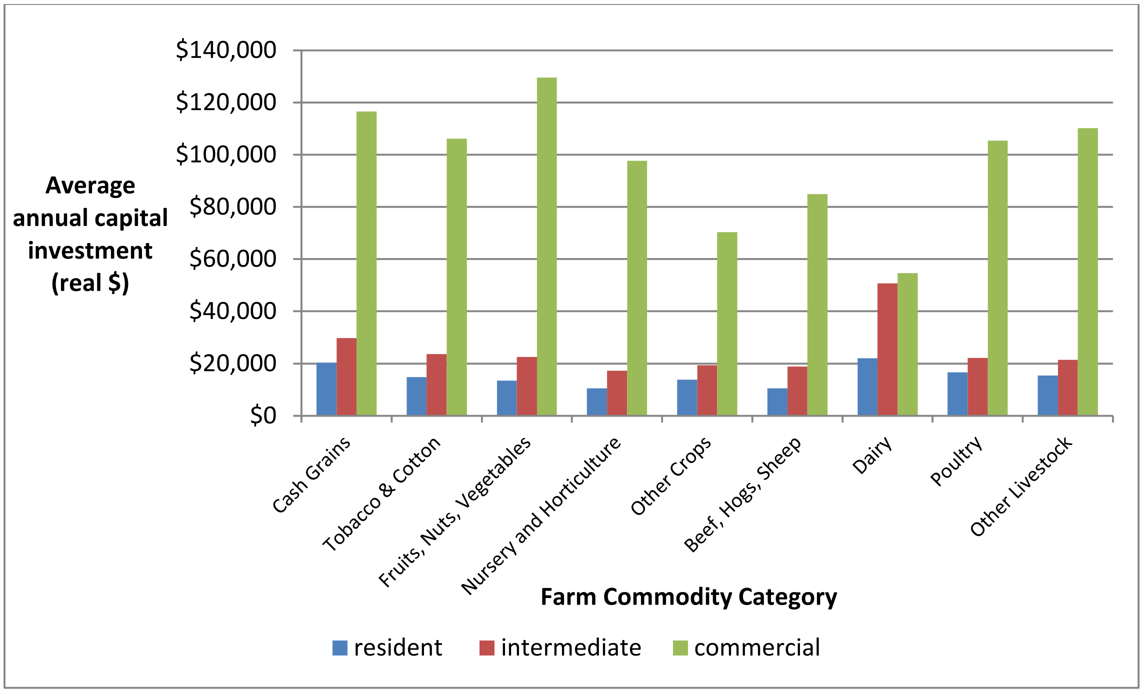

Figure 5: Average[10] Expenditure on Machinery, Equipment and Structures within a Given Survey Year on Farm Capital by Commodity Type[11] and Farm Typology during 1996-2013

The annual average investment level was larger for grain, fruit and vegetable, and poultry commercial farms compared to dairy, beef cattle, and hog commercial farms. Similar patterns exist across other farm typologies, except for dairy, where resident and intermediate average investment levels were larger than that of resident and intermediate farms in other commodity types. Similar to between regions, there is a greater degree of variance in commercial farm investment levels across crop type compared to resident and intermediate farms.

[10] Sample observations are weighted by their percentage of the US farm population

[11] Farms are grouped under a specific commodity if more than 50% of the farm's sale revenues in a given year are from that commodity. If no single commodity comprises more than 50% of the farm's revenues, then they are classified either under grain or "other" livestock.

CHAPTER 3: LITERATURE REVIEW

There is a rich history within agricultural economics of studying the demand for agricultural machinery and equipment, going back to Cromarty (1959) whom looked at the factors influencing the demand for farm machinery in the U.S. from 1920-1955, a time of great transition within the agricultural sector. Subsequent studies focused on the question of what determines the demand for agricultural equipment, but incorporated developments in the theory to examine issues of long run vs. short run adjustment and elasticities, the relative demand for types of capital goods and in relation to labor and other inputs, quasi-fixed assets and adjustment costs, the impact of taxes, and technological change. These included Abebe Dahl Olson (1989), Jorgenson (1963), Kolajo and Adrian (1986) and Lopez (1980). These studies employed aggregate economy wide data time series datasets and the neoclassical approach proposed by Jorgenson (1963), where farm machinery demand is solved by optimizing a production or cost function. Most of these early studies assume perfect capital markets (Fuzzari et al., 1988). Under this scenario, real firm decisions are independent of financial factors. All farms have equal access to capital and are able to purchase the optimal level of farm machinery to maximize profits so that external funds are a perfect substitute for internal capital (Fuzzari et al., 1988). This assumption was first relaxed by Hubbard and Kashyap (1990) using Euler equations on aggregate US farm investment data from 1914-1987 to model the impact of changes in cash flows on farm capital investment. Further extensions to this model have been employed in subsequent panel data studies and are covered below.

3.1 Early Literature and Changes in Tax Policy

In particular, one early addition to the literature and relevant to my study was incorporating the impact of taxes. These examined the impact of taxes and the difference in predicted vs. actual investment and capital stocks via the change in the implicit price, or user cost of capital caused by a change in either tax rates or depreciation tax policy, as outlined by Hall and Jorgenson (1967) for non-agricultural capital. This wave of literature was prompted by significant changes in the tax code in the 1980's under the passage of the Tax Reform Act of 1986 (TRA). Examples include Halvoresen (1991), Hanson and Bertelsen (1987), LeBlanc and Hrubovcak (1986), LeBlank et al (1992). Overall they find that changes in the tax code have significant impacts on the level of implicit prices and capital stocks and the level and timing of investment, though the impact varies by farm size, production type and asset type (Hansen and Bertelsen, 1987), the level of asset fixity assumed (Halverson, 1991), and if one allows for time varying coefficients or not (Conway et al., 1987). In contrast to the econometric methods used in the prior studies, Smith (1990) and Mauer and Ott (1995), examined the impact of investment tax credits, depreciation rates, and marginal tax rates on investment timing for agricultural and non-agricultural machinery using asset replacement models and numerical analysis. They also find that tax code policy changes have significant impacts on the level and timing of investment.

3.2 Use of Cross Sectional and Panel Data Studies

Many of the initial studies which examined the impact of prices, tax policy changes, interest rates and measures of farm asset and debts on investment relied on time series data. With the advent of cross sectional and panel level datasets, it is possible to link investment behavior to differences in specific farm variable levels and differences. Taking advantage of these datasets, further capital investment studies have addressed the impacts of cash flows (Jensen et al., 1993) and farm credit constraints (Ariyaratne and Featherstone, 2009; Barry et al., 2000; Bierlen and Featherstone, 1998; Hüttel et al., 2010;; Serra, 2003), tax policy (Gustafon et al. 1988; Hadrich, 2013; Venzetti and Quiggin, 1985), and adjustment costs (Micheels et al., 2004).

3.2.1 Cash Flow

Drawing on the work of, Hubbard and Kashyap (1990), whom estimated statistically significant relationships between cash flow and U.S, farm investment using aggregate data over the period of 1910-1978, Jensen et al. (1993) added internal cash flow variables to a panel data level model of Kansas farm investment during 1973-1988 to determine if these variables, and other farm specific identifiers such as operator age and type of business, could improve farm investment models. They conclude that in addition to traditional neoclassical variables used in previous studies, additional internal cash flow measures, such as lagged profits, interest expenses, and off farm income levels were significant in explaining investment levels. In a similar exercise, Weersink and Tauer (1989) added cash flow variables using an flexible form accelerator model to Dairy farm investment and compared this to solving a dynamic optimization problem. They similarly found cash flow measurements significant in explaining farm capital investment.

3.2.2 Credit Constraints

Credit constraints are linked to the theory of asymmetric information and imperfect capital markets. Due to asymmetric information between borrows and lenders or lack of collateral, obtaining loans may be expensive or prohibitive. Reflecting the pecking order of the hierarchy of finance, external funds become more expensive than internal funds. Lack of internal funds may lead to an inability to invest. As a result, farm investment on credit constrained farms becomes sensitive to fluctuations in the level of internal funds (Berlien and Featherstone,1998; Gilchrist and Himmelberg, 1995; Hubbard and Kashyap,1992; Jensen et al., 1993). When profits are high the cost of funds is low and farms invest. When profits are low than the cost of internal funds are expensive/probative and investment goes down. A common exercise has been to compare the behavior of credit constrained farms with farms judged a prior to be non-credit constrained. Extensions for this model include controlling for the impact of outliers (Hart and Lence, 2004), differences in credit constraints across countries (Benjamin and Phimister, 2002; Hüttel et al., 2010), and risk (Bokusheva et al., 2007; Sckokai and Moro, 2006)

3.2.3 Adjustment Costs and Real Options

Credit constraints are one reason for lags in adjustment in investment (Berlien and Fetherstone, 1998; Hubbard and Kashyap, 1992; Jensen et al., 1993). Others include adjustment costs or real options (Boetel et. al., 2007; Hüttel et al. 2010; Serra et al. 2009). Under the former, assets are fixed or quasi fixed and there are fixed costs associated with adjusting the capital stock (Boetel et. al., 2007, Vasavada and Chambers, 1986) while under the later the decision not to invest becomes rational given uncertainty regarding the future. Within the panel data literature areas of emphasis include determining optimal lag adjustment structure of farm capital investment (Trevena and Keller, 1974), or employing threshold adjustment models (Guastella et al., 2013; Serra et al. 2009), tobit models (Hüttel et al., 2010) or error correction models (Bokusheva, 2007) to model real option behavior.

3.2.4 Tax Policy

Moving to panel data, Hadrich et al. (2013) estimated the impact of a change in the Section 179 limit on the probability and resulting level of capital investment for farms in the North Dakota Farm and Ranch Association during the period 1993-2011. They find that increases in the section 179 limit significantly increased the probability of investing and the investment rate. Similarly, Ariayante and Featherstone (2009) also find that depreciation tax levels have a significant impact on farm capital investment, though the impacts are remarkably different across types of capital. In contrast, other panel data studies find tax code changes have little impact on farm capital cite the importance of expected profits (Vanzetti and Quiggin, 1985) and other financial and structural characteristics (Gustafson et al 1988) in determining investment.

3.3 Differences in Investment Across Farms by Category

Since the focus of my research is differences in the responsiveness to U.S. farm capital investment by farm size, when reviewing the literature on U.S. farm capital investment I searched for studies which estimated the impact of changes in key variables on investment separately by measures of farm size and/or related categories. I found three which fit this criteria. They are summarized below.

Using Illinois Farm Management data on farm investment during 1987-1994, Barry et. al. (2000) compare farm investment for different groups based upon age and different financial ratio criteria. They utilize a tobin q model, where the fundamental return to investment is estimated and distinguished from cash flows available to the firm. They find that investment levels are more sensitive to changes in cash flow movements for younger producers and those with weaker financial ratios.

Using a similar methodology, Bierlen and Featherstone (1998) examine the impact of cash flows on farm investment using Kansas Farm Management data from 1976-1992. They separate farms by age, time period and farm debt levels. Sensitivity to cash flow characteristics differed across groups within different time periods. Cash flow variables were generally less significant in determining farm investment during the boom period of the 1970s. They became important for younger farmers with greater farm debt with the downturn in the farm economy in the 1980s and the 1990s. In contrast, older and lower debt farms were less sensitive to credit constraints during the 1980s and 1990s.

Ariayante and Featherstone (2009) also split farms into categories based upon farm size to examine relative impacts of government payments, depreciation expense levels and inflation on investment for farms as a whole and across different asset and age quartiles. They utilized Kansas Farm Management data over the period of 1998-2007. Investment across all farm categories were significantly related to lagged crop and livestock income and depreciation expenses. The impact of government payments and interest expenses varied by farm asset level and operator age. Investment was not responsive to changes in government payments for farms with larger asset levels and for operators in the youngest or oldest age quartiles but was but was for farms with operators in the middle age quartile or for farms with smaller asset levels. Investment decreased with increases in interest payments for farms in all age quartiles and farms in the smaller asset quartile but had no impact on farms in larger asset quartiles.

3.4 My Additions to the Literature

This study adds to the current literature in two ways. First, this study examines how the factors driving farm investment differ across farm typologies, accounting for both differences in gross cash farm income levels and primary operator occupation type. None of the prior studies has examined how differences in the primary occupation of the farm operator could influences differences in farm investment. I believe that occupation type has an impact on investment, and that by distinguishing farms earning smaller farm incomes by occupation type, I can obtain more accurate estimates of investment.

Utilizing the ARMS data to study farm capital investment is another unique aspect of my research. The ARMS is currently used to develop congress mandated: estimates of commodity costs and returns for specific commodities, estimates of net farm income for commercial producers across specific farm types, an index of prices paid by farmers, and a report on demographic and structural information and trends for family farms (Kuethe and Morehart, 2012). While the ARMS has been utilized by researchers to study a variety of issues, including but not limited to technology adoption, structural change in agriculture, the economic health of and trends within the farming sector, and to comparisons of farm household and non-farm households across different measurements (Kuethe and Morehart, 2012), it has not been utilized to study farm capital investment, with the exception Stutzman and Williamson (to be published). The majority of the farm capital investment literature utilizes either aggregate time series data or state/region wide farm panel datasets. Compared to the ARMS, these state/region wide farm panel datasets, have fewer observations, cover a limited geographic region, and/or provide less detailed farm business and household financial data. The ARMS is the only annual national survey of US farms to provide detailed information regarding farm level production practices, financial performance and household information (Kuethe and Morehart, 2012; National Research Council, 2008). It provides information on a wide range of the business and farms making up the farming sector, included many small part-time and limited resource operations as well as large farms with sales in the millions (Kuethe and Morehart, 2012). By utilizing the ARMS I am able to provide a unique and necessary picture of the farm capital investment behavior of farms across the whole U.S. as well as distinguish between differences among farms according to key production, financial, and farm household characteristics.

CHAPTER 4: THEORETICAL INVESTMENT MODEL

In this section, I derive a theoretical model from a dynamic optimization problem solved for the optimal long run level of capital stock, explain my choice of variables included in the model and specify the reduced form model that I will estimate.

4.1 Deriving the Flexible Accelerator Model

A model of investment based upon the flexible accelerator theory can be derived by solving a profit maximization problem. Under the profit maximization problem, a firm makes an investment in machinery to maximize the net present value of expected cash flows from the investment. Using a dynamic model, this can be written as:

Maximize $V_0 = \int_{t=0}^{L} R_t \, e^{-rt}$ where $R_t/P_t. = G(W_t, X_t, K_t) - C(\frac{dK}{dt})$; $\frac{dK}{dt} = I_t - \varphi K_{t-1}$ (1)

where (V_0) is the net present value of cash flows over the life of the investment, based on R_t, the returns from investment in year t, the discount rate r, and the life of the asset L. R_t is the difference between a long-run unit-output profit maximization function, G_t (W_t,X_t,K_t) and a short run-capital cost adjustment function, C(dK/dt). Both the profit maximization function and the capital cost adjustment function are normalized by output price, P_t. Profits are a function of the chosen level of a quasi-fixed level of capital stock (K_t), other variable inputs, X_t, and variable input prices, W_t. This is reduced by the costs involved in adjusting the level of capital stock. This is represented by the cost adjustment function, C(dK/dt), which states that the cost of adjusting to a new level of capital is a function of the change in capital between time periods, dK/dt. This assumes that the marginal cost of existing capital stock is constant between time periods and changes in the marginal cost of capital occur only when the capital stock level is altered. Reasons for changing marginal costs include financing concerns, additional training, or equipment downtime.

An equation of motion, dK/dt, links capital stock levels between periods. The equation of motion states that the change in capital between periods is equal to gross investment, I_t, less economic depreciation of capital stock, φK_{t-1}. I assume that economic depreciation is equal to a fixed portion, φ, of the previous period's capital stock, $K_{t-1.}$ In each period, the firm chooses the capital stock, K_t and other inputs, X_t, given the equation of motion governing the change in capital over time, $\frac{dK}{dt}$, to maximize the net return to investment V_0. Assumptions include myopic or stationary real input and output price levels, other variable inputs are completely flexible, and firms are price takers in the input and output markets. LeBlanc et al., (1992) outline how by choosing a profit and cost function and solving the Hamiltonian one obtains a numerical solution for the short-run demand for capital, K_t. This is equivalent to the approximate solution to the demand for K*, which is the steady state or long-run profit maximizing demand for capital. K* is the optimal capital level or the capital level the firm would choose given no barriers, time lags, financing constraints, or other delays in adjusting the capital stock given changes in economic conditions or other factors affecting the demand for capital. The long-run solution to K* using dynamic programing obtained by LeBlanc et al. (1992) and Weersink and Tauer (1989) is equivalent to the long-run demand for capital as expressed by accelerator theory.

From this the demand for gross investment is derived. This is referred to as the flexible accelerator theory of investment. Gross investment becomes the change in the capital stock between periods. This can be expressed in discrete time as:

$$I_{i,t} = K_{i,t} - K_{i,t-1} = alpha[K_{i,t}^{*} - K_{i,t}] \text{ where } NI_{i,t} = (K_{i,t} - K_{i,t-1}) - \varphi K_{i,t-1} \qquad (2)$$

where $I_{i,t}$ is gross investment, $NI_{i,t}$ is net investment, and φ is the rate of economic depreciation. Gross Investment ($I_{i,t}$) is proportional to the difference between desired capital, $K_{i,t}^{*}$, less capital stock levels in the prior period, $K_{i,t-1}$, times an adjustment factor, alpha. Net Investment ($NI_{i,t}$) is equivalent to gross investment less the portion of the previous capital stock that needs to be replaced due to wear or tear ($\varphi K_{i,t-1}$). Adjustment is instantaneous under neoclassical theory. Changes in factors affecting the long run level of capital, K*, are fully manifest in a change in investment in the given period. This is equivalent to stating that the value of alpha equals one. If alpha does not equal 1, than within a given time period the capital stock does not fully adjust to the long-run level. Full capital adjustment instead takes multiple time periods. This means that changes in previous economic conditions have impacts on investment beyond the current period.

Following in the footsteps of Jensen et al., (1993) and others I start directly from the flexible accelerator theory and obtain a reduced form model for capital investment. Economic theory and previous literature provides a basis on the choice of variables to proxy $K *_{i,t}$ and adjustment costs. Different methods for modeling the adjustment factor and desired farm machinery stock have been suggested by Conway et al (1987), Girao et al. (1974), Jorgenson and Seibert (1968), Trevena and Keller (1974), and Weersink and Tauer (1989). Treveno and Keller (1974) compared the results from solving the dynamic optimization problem with estimating the reduced form flexible accelerator model and found that they performed similarly. Using a reduced form accelerator, one does not have to specify a specific functional form for profits or costs. Additionally, utilizing this model allows the incorporation of factors affecting investment beyond the prices and quantities of outputs and inputs and including lagged independent variables to represent linkages between internal funds and investment levels over multiple periods.

4.2 Representing Changes in the Optimal Level of Capital Stock

Economic factors driving changes in the optimal level of capital stock included in the model are outlined below. These include changes in output prices, net cash farm income, tax depreciation, marginal tax rates, farm size, specialization, and technological change.

Output Prices (PrIndex)

According to neoclassical theory, the demand for inputs into the production process is a function of output prices. This follows from the accelerator theory of investment. Under this theory, increases in the demand for output lead to increases in output prices. Producers respond to higher output prices by increasing production and output levels.

Net Cash Farm Income (NCFI)

Under the profit theory of investment, the optimal level of capital stock is influenced by the returns earned from investment. This follows from the initial profit maximizing equation above. Firms choose a level of capital to maximize the returns from investment, or the income earned per unit capital stock. A change in output prices and/or input prices leads to direct changes in the quantities produced and/or shifts among either outputs and/or inputs to maximize expected returns to investment. Greater potential returns to investment are expected to increase firm investment level.

I measure the returns to investment as net cash farm income per unit capital stock. Net cash farm income is gross cash farm income less operating expenses. Gross Cash farm income includes revenues from the sale of farm productions, inventory adjustments, government payments, custom work income, incomes from land rented to others, incomes from livestock or crops removed under production contracts, and payments from royalties and leases for energy production. Expenses include labor, land rental, hire custom work expenses, capital equipment leasing fees, and others. This measurement does not include non-cash labor expenses, depreciation expenses, or the returns to operator's time and management.

The expense items included to calculate net cash farm income, such as labor, land rental, hire custom work expenses, and capital equipment leasing fees, are highly correlated with investment. Unfortunately, within the ARMS dataset, these items are also strongly correlated with each other and with net cash farm income levels, leading to multicollinearity and other estimation problems. Utilizing a single measure of net cash farm income to capture the impacts of these different cost items minimizes the number of additional variables in the regression model and multicollinearity issues. Unfortunately, it limits my ability to discern the individual impact of each item separately.

Depreciation Expenses (DEP) and Marginal Tax Rates (MTR)

According to Jorgenson's neoclassical theory of investment, changes in the user cost of capital impact the level of capital demanded by the firm. The user cost of capital is determined by equating the marginal value product of capital with its user cost. The marginal value product of capital is the extra revenue earned by a unit of capital while the user cost is a function of the asset's purchase price adjusted for interest expenses and the tax benefits of owning capital. These tax benefits include depreciation tax deductions and reductions in total farm household tax levels. An increase in allowable depreciation expenses and a larger farm marginal tax rate will decrease the after-tax cost of capital. This makes capital relatively less expensive and should lead to increases in investment.

In theory, the user cost of capital should reflect the individual cost of each specific unit of capital. Different individual purchase prices, interest rates, and depreciation rates will result in very different implicit prices for different capital units and resulting impacts on investment. Unfortunately, the ARMS survey does not consistently collect data on the number and specific type of capital unit per farm across survey years. The survey does not ask producers to provide information on prices of individual capital items nor their use within different farm enterprise production activities. As a result, it is not possible to link revenues, output prices, interest payments, nor depreciation deductions with individual physical units of capital. As a result, I capture the impact of taxes on farm investment by utilizing the farm's total annual tax depreciation expense and marginal tax rate. Interest expenses are accounted for in the measurement of net cash farm income.

Farm Size (Acres)

The annual capital replacement level is directly related to the number of acres operated. Larger farms will require greater investment levels to maintain existing capital stocks. An increase in the number of operated acres should lead to an increase in investment in the current period as well as in future periods. The degree of which capital needs change as farm acreage increases will differ across farms depending on commodity type, regional geography, and returns to scale. Given an expansion of farm size, increasing returns to scale will result in a less than proportional increase in investment expenditures per acre while decreasing returns to scale will lead to more than proportional investment per acre.

Specialization (Entropy)

Specialization, defined as the total number of crops produced and relative portion of each within the farm's crop mix, will impact the level of farm capital investment. Adding additional crops to the farm's crop mix is expected to increase capital investment. The degree to which gains to or disadvantages to scope are present will influence how much additional investment is needed. If specialization in fewer crops results in more efficient use of current machinery, then investment per unit of output will decrease as specialization increases. If instead diversification allows the farm to reduce total capital required per acre, for example by reducing machinery downtime and taking advantage of different crop planting and harvest schedules, then diversification will result in reduced investment per acre.

Technological Change

Over time, changes in technology alter the profit maximizing level and type of capital. The impact of technological change on annual investment is proxied by dummy year variables. The use of individual year variables allows the impacts of technological change to vary differently depending on the year. In addition, these dummy variables capture other unobserved year specific impacts. Using a linear time trend assumes a constant marginal impact of technological change on investment over the given sample period. Considering diversity of commodities produced and geographic regions within the ARMS data, as well as changes in US farming over the 18-year sample period, assuming non-constant technological change is the most logical choice. In practicality, a linear time trend is often insignificant while individual time dummy variables are statistically significant and different across years.

4.3 Representing Changes in the Adjustment Rate

Under the theory of perfect capital markets, firm financing is irrelevant in the investment decision. If markets are not perfect than the level of internal funds becomes an important factor determining farm investment levels. This is due to either constraints in the amount of funds firms can borrow or increasing costs as a function of firm borrowing levels. If imperfect capital markets are assumed, farm investment may increase or decrease depending on changes in internal measures of cash flows. Previous studies have found internal cash flow variables have a significant impact on farm investment levels (Ariyarante and Featherstone, 2009; Bierlen and Featherstone, 1998; Hadrich, et al., 2013; Jensen et al.; 1993; and Weersink and Tauer, 1989). These cash flow measures will impact the rate at which the capital stock is adjusted to the new optimal level. Included cash flow variables are off-farm income, liquidity, and interest rates.

Off-farm income (OFFI)

Off-farm income is an indicator of additional cash flow available to the farm for investment. Greater off-farm income results in higher levels of internal funds available for farm investment. As a result, increases in off-farm income is expected to increase farm investment.

Working Capital (WC)

Farm liquidity represents another measure of internal funds available for investment. Farm liquidity is represented using working capital, which is measured as current assets less current debts. This represents the level of short-term assets available each period after current debt obligations have been met. For farms which are credit constrained, a greater level of liquidity should increase investment.

Interest Rates (IR)

Interest rates impact the cost of borrowing and the opportunity cost of investment. Increases in interest rates will make investment more expensive and should decrease the level of investment. Farm interest rates are linked to broader overall national economic trends including GPD levels and inflation. By including interest rates in the model, the model captures some element of the broader macroeconomic forces affecting farm machinery demand.

4.4 Reduced Form Flexible Accelerator Model

Incorporating the above variables into the flexible accelerator model in (2) and assuming a linear functional form results in the following model:

$$\frac{I_{i,t}}{K_{i,t}} = F(PrIndex_{i,t}, \frac{NCFI_{i,t}}{K_{i,t}}, \frac{DEP_{i,t}}{K_{i,t}}, MTR_{i,t}, \frac{ACRES_{i,t}}{K_{i,t}}, Entropy_{i,t}, Year_t, OFFI_{i,t}, \frac{WC_{i,t}}{K_{i,t}}) \qquad (3)$$

Investment is a function of output prices, net cash farm income, depreciation, the tax rate, farm size, specialization, off-farm income, working capital, and the specific year. Following the example of Ariyaratne and Featherstone (2009) and Barry et al. (2000) relevant variables, which included investment, net cash farm income, depreciation expenses, acres and working capital, were normalized by the level of farm capital, $K_{i,t}$. This reduces the level of heteroscedasticity that would be otherwise caused by differences in revenue and expense levels between farms related to differences in farm sales. The interpretation of these variables alters slightly due to this normalization. Investment is no longer the dollars invested per year but instead the rate of replacement of the gross capital stock, income is income earned per unit of capital, depreciation expenses is the average depreciation taken on a unit of capital that year, working capital is the level of working capital per unit capital stock, and acres is no longer total farm acres but the average acres operated per unit capital. This model is estimated using pseudo panels constructed from the ARMS survey data. In the next section I provide background on pseudo panel theory, construction, and estimation methodology.

CHAPTER 5: PSEUDO PANELS AND DATA SOURCES

In this section I provide a description of pseudo panels, the literature supporting their usage, my methodology for constructing pseudo panels from the ARMS data and compare the resulting pseudo panel measurements with the survey data.

5.1 Reasons for Construction

The cross sectional nature of ARMS provides information only on the decision of a single producer to make a capital purchase in a given year. There is no way of knowing from the data if the same producer made an investment last year or will make an investment next year. This prevents the linkage of investment behavior over multiple time periods. In addition, there is no way to connect changes in the levels of the model variables in prior periods with investment choices today. Believing that I will attain more accurate estimates by examining the investment behavior of similar farm types over multiple time periods rather than individual farms at a single point in time, I construct a synthetic panel using the ARMS data. My methodology is based upon established theory developed for construction and estimation using synthetic panels constructed from survey data. These panels are often referred to as pseudo panels.

Deaton (1985) introduced pseudo panels as a means to construct panel datasets from balanced or unbalanced survey datasets. He outlines the conditions for which one can utilize pseudo panels to consistently estimate population effects. These conditions were further tested and expanded upon in by Verbeek and Nijman (1993), Moffitt (1993), Verbeek and Vera (2005), and McKenzie (2004). Utilizing these findings, authors have explored economic relationships using pseudo panels constructed from large surveys such as the US Census (Russell and Fraas, 2005).

Previous studies have constructed pseudo panels using ARMS data. For example, Blank et al. (2004) constructed pseudo panels to examine differences over time in risk attitudes for corn and soybean producers using ARMS data from 1996-2001. O'Donoghue and Whitaker (2010) examined farm payments and acreage planting decisions using pseudo panels constructed from ARMS data for survey years 2000-2001 and 2003-2004. To look at the impact of production contracts on productivity, efficiency and scale economies Morrison-Paul et al. (2004) formed pseudo panels using 1991-2002 ARMS survey data. Finally, to determine if marginal rates of consumption differ by type of government payment, Whitaker (2009) formed pseudo panels using ARMS observations from survey years 1998-2004.

ARMS data has many advantages over other farm management panel data sets. The ARMS dataset is geographically more representative of the U.S. farm population, covers a greater number of farms, and is more detailed than most existing farm panel data sets available. By constructing pseudo panels from cross sectional data much of the attrition bias found in panel datasets is eliminated. Using ARMS data to study farm behavior overtime would allow us insights into many questions concerning the impacts of different policies. Unfortunately, currently many important policies are not studied using ARMS data due to the inability to track farms over time (Featherstone et al., 2012). The results of my work into pseudo panel data can assist others in utilizing ARMS data to estimate dynamic panel models of farm behavior.

5.2 Construction of Pseudo Panel Dataset 1

Creating pseudo panels involves grouping farms with similar characteristics into groups, referred to as cohorts. The mean values of observations are calculated within each cohort and for each year. Estimation is performed on these mean values.

An important decision when forming pseudo panels is the categories to use to split individual farms into groups. There are two main considerations. The first is forming time invariant groupings. This requires that the probability of the same farm being placed in a given cohort is independent of the survey year. The second is making sure that the groupings are heterogeneous enough to determine different impacts from changes in the dependent variables while making sure that they still reflect the true population means. I choose categories to maximize the heterogeneity between cohort observations and maximize the homogeneity of observations between farms in the same cohort (Whitaker, 2009).

I group farms according to commodity type, geographic region, and typology. These categories are summarized in Table 7 and described in more detail below.

Table 7: Categories Used to Form Pseudo Panel Cohorts in Panel Dataset 1

Farm Typologies	Prodution Type	NASS Farm Production Expenditure Regions
•resident •intermediate •commercial	•cash grain •tobacco and cotton •fruit, nut and vegetable •nursery and greenhouse •other crops •beef, hot and sheep •dairy •poultry •other livestock	•West •Plaines •MidWest •Atlantic •South

Previous studies using ARMS data have used similar categories such as: 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). These categories are similar to the ARMS stratified sampling divisions of state, farm type and farm size. Using categories that take into account the ARMS sampling design should provide more accurate cohort estimates. In addition, farm investment and other variables such as revenues, expenses, asset and debts differ according to region, commodity type, and typology. By taking cohort means within these categories the cohort means will reflect important distinctions within the sample data.

The next consideration is how many categories to utilize. In compiling the data, ERS researchers split farms into 19 commodity groups depending on the share of farm revenue earned by commodity. Farms are then grouped into smaller commodity categories by combining similar commodity groups. When choosing the number of commodity types there is a trade-off between making sure that I am not taking averages over distinctively different commodity types while keeping the time-invariant nature of my sample. For example, splitting farms into separate categories for corn and soybean farms would most likely result in farms moving between cohorts in alternative years and as a result provide inconsistent estimates. On the other hand, separating corn and soybean farms from dairy farms should not result in farms moving between categories depending on the year. I choose to group farms into 9 commodity types. I am fairly confident that these divisions capture key differences between farm observations by production type while retain the time invariant nature of the pseudo sample. The commodity types are listed in table 2.

Larger geographic regional distinctions are created by combining farms within each of the 48 surveyed states by state and/or similar geographic regions. I choose to utilize the five NASS Farm Production Expenditure Regions. See table 2 for a list of the regions. A map of the regions is provided in Figure 6.

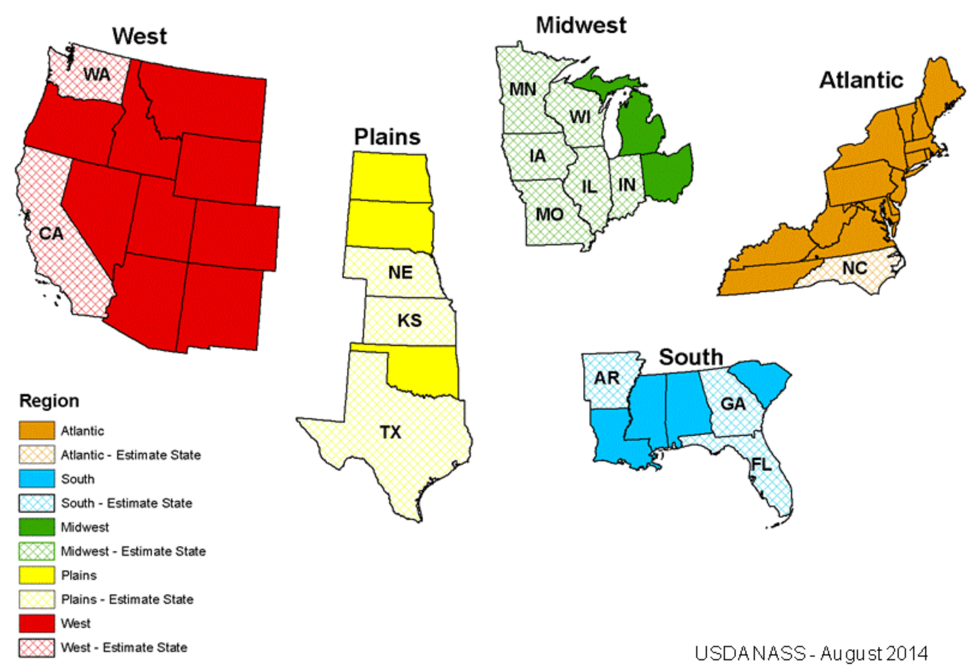

Figure 6: Map of NASS Farm Production Expenditure Regions

I am fairly confident that these categories are relatively time invariant. It is unlikely that more than a few farms will move geographically between regions over the sample period. On the other hand, the regions are different enough to capture significant regional variations between farms.

Finally, I use three typology categories to reflect differences in farms according to farm size. Using economic size categories to take advantage of the stratified ARMS sampling was suggested by Featherstone et al. (2012). Blank et al. (2004) and Morrison-Paul et al. (2004) constructed cohorts using farm typologies. Technically, this category is not completely time invariant. While there may be some switching between the resident and intermediate categories as farmers retire and either leave or enter farming full time, the greater concern may be farms moving between the commercial category and either resident or intermediate categories based on annual fluctuations in farm income. Fluctuations in farm income will be due to fluctuations in both aggregate level agricultural price cycles and farm level yields. This will most likely be an issue for larger intermediate or resident farms and smaller commercial farms. The alternative, not splitting farms into categories based upon typologies, would result in cohort means being averages of farms within these different categories. This is problematic. Average values within these categories are very different. Taking means across these categories creates cohort means not reflective of the true underlying sample values. To account for the potential of farms moving between cohorts due to using farm typologies, the estimates obtained using this cohort formation will be compared with cohort formations that do not split farms based upon farm income levels. This is explained in more detail later.

The final decision is to employ the ARMS weights or not when forming cohort means. Whitaker (2009) and Blank et al. (2004) also employed ARMS expansion weights within their analysis. Other studies choose not to apply the weights. This reflects the overall mixed opinion in the literature regarding using survey weights when constructing subsamples from stratified larger samples. If the cohort formation process is reflective of the stratum category division, using the weights should provide better estimates of the means within cohorts. This is particularly important as ARMS does not sample the same farms or even the same composition of farms each year. They rely on the sample weights to make sure that all farm types are accurately accounted for. Using the sample weights ensures that farm estimates in each year are more likely to represent the true population mean values in a given year. Using sample weights also alleviates the problem of heterogeneity within cohort means due to unequal sample sizes across survey years. On the other hand, if only the behavior of the sample is of interest the weights may distort the estimates (Dubman, 2000). A benefit of stratification is to reduce the variance of estimates. Categorizations not correlated with strata categories may not reflect the benefits of stratification (Dubman, 2000). After considering the tradeoffs, I decide to apply the ARMS weights. My decision is further supported by the resulting sample estimates. Within the different typology categories, the cohort sample means are similar to the weighted sample means and reflect important differences between resident, intermediate and commercial farms. Similarly to using the weights when calculating mean and standard error estimates for survey mean values, employing the weights when taking the cohort means results in lower overall mean and standard error estimates.

I take the weighted mean of the relevant variables across farms within the same region, production type, and typology category. This creates an unbalanced panel dataset of 2,341 total cohort observations. Within each region, production type and farm typology over time and within time between cohorts the number of observations used to construct the cohort means vary, as seen in Table 8-Table 10.

Table 8: Average Number of Farm Observations Used to Calculate Resident Farm Cohort Means

	Region				
Production Type	Atlantic	South	Midwest	Plains	West
Cash Crop	33.3	22.3	186.2	69.1	17.7
Tabaco and Cotton	25.6	9.9	1.6	3.7	0.3
Fruit and Nut	24.4	31.4	15.5	8.0	72.7
Vegetable and Horticulture	23.6	11.2	10.7	3.2	13.6
Other Grain	188.0	226.7	154.9	248.5	125.1
Beef and Hogs	4.2	2.9	9.3	4.7	3.8
Dairy	10.9	8.6	6.4	3.7	4.3
Poultry	5.3	0.9	8.2	1.0	0.9
Other Livestock	189.7	134.9	238.1	195.9	188.8

Table 9: Average Number of Farm Observations Used to Calculate Intermediate Farm Cohort Means

	Region				
Production Type	Atlantic	South	Midwest	Plains	West
Cash Crop	52.9	48.9	314.6	195.9	77.6
Tabaco and Cotton	42.4	30.8	2.0	22.9	2.4
Fruit and Nut	38.8	31.9	22.7	6.8	104.4
Vegetable and Horticulture	33.7	26.9	14.6	4.1	22.0
Other Grain	110.9	158.7	108.8	241.4	176.7
Beef and Hogs	3.7	2.4	15.9	3.2	1.6
Dairy	17.1	18.3	4.8	3.7	2.3
Poultry	89.9	9.8	118.7	9.2	10.3
Other Livestock	84.7	62.8	91.9	96.9	134.0

Table 10 Average Number of Farm Observations Used to Calculate Commercial Farm Cohort Means

	Region				
Production Type	Atlantic	South	Midwest	Plains	West
Cash Crop	71.2	135.1	461.4	220.4	99.9
Tabaco and Cotton	39.1	85.0	3.8	36.5	9.7
Fruit and Nut	35.9	40.4	24.7	6.1	163.2
Vegetable and Horticulture	42.9	50.8	30.6	7.7	44.1
Other Grain	16.8	18.3	45.2	131.1	87.6
Beef and Hogs	36.8	7.7	79.8	8.8	1.1
Dairy	139.5	251.7	36.8	37.9	9.3
Poultry	136.0	25.9	151.5	29.4	134.5
Other Livestock	29.3	59.0	42.1	35.3	94.8

Variation in the number of farms comprising cohort means is due to both the increasing scope of the ARMS sample over time as well as the stratified nature of the ARMS survey. As time progressed the overall number of farms sampled has increased, as demonstrated in Table 1. In addition, some categories are sampled more heavily generally due to a greater number of available farms within that production category, region and farm typology class. ARMS is used to construct estimates for US farm income and expenditure estimates and given the importance of commercial farms in determining these figures as well as their greater ability to be located, a greater number of commercial farms are sampled compared to resident and intermediate farms. Within certain regions, and in particular among large farms, there may be few or zero farms that earn greater than 50% of their farm income from that commodity or livestock category. This creates an unbalanced pseudo panel. Missing cohort values occur to a greater degree among resident an intermediate farms compared to commercial farms and in more defined livestock and commodity categories such as tobacco and cotton grown in the Midwest and Western U.S. Other specific categories having missing observations in some years included resident poultry farms, intermediate beef and hog farms outside of the Midwest, or commercial beef and hog farms in the Western U.S.

5.3 Data Sources and Variable Construction

Data on capital expenditures, farm capital stock levels, net cash farm income, tax depreciation expenses, farm acreage, specialization levels, off-farm income, and working capital levels are obtained from the ARMS. See section 2.1 for more details on the ARMS procedures and methodology. Revenues, expenses, and income measures totals earned or spent over the course of the survey year from January 1st to December 31st. Asset, debt and net worth values represent the dollar value of the item in question as of December 31st of the given survey year. All dollar values are adjusted to 2012 real values using the CPI data available from the Bureau of Labor Statistics.

The ARMS collects data on total revenue and expenses but not individual input or output prices. To obtain a measure of output prices, I construct a price index ($\mathrm{PrIndex}_{i,t}$). I obtained data from NASS Quick Stats and from the USDA Annual Survey of Horticulture Producers on annual output prices for a set of 18 different commodity and livestock categories. These categories correspond to a set of 18 commodity types into which farms in the ARMS are divided. The division is based upon revenue levels. If farms receive more than 50% of their yearly sales from commodity(s) within a given category they are classified as under that category. The “other crop” or “other livestock” category is used for farms for which less and 50% of revenues fall under one of the specific crop or livestock categories. Within each year for each cohort, the index price for each commodity category was multiplied by the portion of sales within that category. A list of the commodity types and price data used is provided below in Table 11.

Table 11: Price Index Variable Construction

ARMS Code	Commodity	Data Used	Notes on the ARMS classifications
1	General Cash Crop[1]	Average of price indexes constructed for: Corn, Soybeans, Sorghum, Oats rice received ($/Bu), Barley price received ($/Bu), Rice, Wheat	Producers are classified as general cash crop if more than 50% of sales are from the cash crops listed but no single item is 50% or more of sales
2	Wheat	NASS Quickstats. Wheat Price Received $/Bu	
3	Corn	NASS Quickstats. Corn Price Received $/Bu	
4	Soybeans	NASS Quickstats. Soybeans Price Received $/Bu	
5	Sorghum	NASS Quickstats. Sorghum Price Received $/Cwt	
6	Rice	NASS Quickstats. Rice Price Received $/Cwt	
7	Tobacco	NASS Quickstats. Tobacco Price Received $/lb.	
8	Cotton	NASS Quickstats. Cotton Price Received $/lb.	
9	Peanuts	NASS Quickstats. Peanuts Price Received $/lb.	
10	Crop Other	NASS Quickstats. Crop Totals Index for Price received, base year 2011	Includes sugarcane, sugar beet, crp pasture, maple syrup, mint, grass seed, hops, hay, grain silage, straw, Christmas trees, and short rotational woody crops
11	Fruit and Tree Nuts	NASS Quickstats. Fruit and Tree Nut Totals Index for Price received, base year 2011	Includes revenues from fruit, tree nuts, berries
12	Vegetable	NASS Quickstats. Vegetable Totals Index for Price received, base year 2011	Includes revenues from vegetables, melons, sweet potatoes, potatoes
13	Nursery and Greenhouse[1]	NASS Floriculture Crops Annual Summary Reports 1997-2014.	Includes nursery, greenhouse, and floriculture crops
14	Beef Cattle	NASS Quickstats. Cattle /Calves Price Received $/Cwt	Includes revenue from the sale of cattle and calves
15	Hogs	NASS Quickstats. Hogs Price Received $/Cwt	Includes revenue from sale of hogs and pigs
16	Blank	N/A	
17	Poultry	NASS Quickstats. Poultry totals, including eggs, Index for price Received, base year 2011	Includes revenue from sales of poultry and eggs

Table 11: Continued

18	Dairy	NASS Quickstats. Dairy Product totals Index for price Received, base year 2011	Includes revenue from the sale of milk and other dairy products
19	General Livestock	NASS Quickstats. Livestock Totals, Index for price Received, base year 2011	Includes sheep, goats, goat products, equine, and aquaculture

[1] An average price per year was created by multiplying the wholesale price times the portion of sales from each of the following crops: Carnations (cents/stem), Chrysanthemums ($/bunch), lilies (cents/stem), orchids (cents/bloom), roses (cents/stem), geranium flats ($/flat), inpatients ($/flat), pansy/viola flats ($/flat).

Interest rates ($\mathrm{IR}_{\mathrm{i,t}}$) are the fourth quarter loan rates for farm machinery loans per each of the 10 USDA Production Regions. These were obtained from the Board of Governors Federal Reserve System Agricultural Finance Databook. ARMS data on farm income, off-farm income, and IRS federal tax rates and exemption limits obtained from IRS publications were used to construct a farm household federal marginal tax rate ($\mathrm{MTR}_{\mathrm{i,t}}$). Beginning with farm income, I adjust for social security and Medicare taxes on self-employment and social security income, and subtract from total household income estimated deductions for social security payments, domestic production activities credits, health insurance premiums, and other deductions. From this we subtract the larger of the standardized or itemized tax deduction that year to arrive at an estimated farm household federal taxable income. Based upon married or single status, number of dependents, and federal taxable income levels, the federal marginal tax rate of each farm is determined.

5.4 Summary Statistics for Pseudo Panel Dataset

In this section I examine the summary statistics for the constructed model variables in the pseudo panel dataset. In addition to examining the summary statistics for the model as a whole, I compare mean values across farm typologies and production types as well as the degree of variation between observations within and between variables by farm typologies. Summary statistics for the model variables using pseudo panel dataset 1 are provided in Table 12.

Table 12: Summary Statistics for Variables in Model Using Pseudo Panel Dataset

Variable	Definition	Units	Mean	SD	Min	Max
I [a]	Investment Rate. Dollars spent on farm capital investment divided by capital assets	Ratio	0.0624	0.0577	0.0000	0.7432
PrIndex	Output Price Index. See Data Section and table A11 for more detail	Index	0.7866	0.1920	0.3287	1.2300
NCFI [a]	Return on Assets. Net cash farm income divided by capital assets	Ratio	0.1555	0.2998	-2.6284	4.2015
DEP [a]	Annual tax depreciation expenses divided by capital assets	Ratio	0.0545	0.0584	0.0000	1.2432
ACRES [a]	Farm aces operated divided by capital assets	Ratio	0.0016	0.0026	0.0000	0.0331
MTR	Federal marginal tax rate. See notes above.	Percent	0.1655	0.0700	0.0000	0.3960
ENTROPY	Measurement of farm specialization.	Index	0.1256	0.0968	0.0000	0.4703
OFFI	Off-farm income	1000s Real Dollars	63.57	52.95	-7.38	1,313
WC [a]	Value of current assets less current debts divided by capital assets	Ratio	0.2647	0.4587	-1.8716	8.9960
IR	Interest rates. See Data section for further detail	Percent	0.0704	0.0178	0.0358	0.1070

SD= standard deviation, Min=minimum value, Max=maximum value

[a] Notes variables normalized by farm capital assets. Farm capital assets= total dollar value of assets including machinery, buildings, structures and equipment.

I= Investment= expenditures on buildings, equipment and machinery

PrIndex=index of output prices. For more detail on its construction see data section and Table 11

NCFI=Net cash farm income is gross cash farm income (GCFI) less operating expenses. GCFI includes sales, changes in inventory, government payments to landlord, income from custom work and machine hire, income from royalties and leases for energy production, income from land rented to others, income from crops or livestock removed under production contract, changes in the value of inventories. This measurement does not include non-cash labor expenses or depreciation expenses.

DEP= tax depreciation expenses

MTR= federal marginal tax rate. Includes farm and off-farm income and adjustments for Medicare and social security taxes on self-employment and social security income, deductions including social security taxes paid, domestic production activities credit and an adjustment for health care premiums paid.

ACRES= Physical farm size is measured as the total number of acres operated by the farm. This includes land rented from others and not including land rented to others.

Table 12: Continued

ENTROPY= level of farm specialization. This variable ranks farms on a scale of 0-1, 0 being the most specialized and receiving 100% of yearly sales from a single crop/livestock product compared to 1 the least specialized with all crop/livestock products produced contributing equally to total farm sales.
OFFI= off-farm income. Includes earnings from wages, salaries and self-employment income as well as income from interest, dividends, and social security payments.
WC= Working Capital. Difference in farm current assets less short term debts.
IR= average across farm production regions of the interest rate on farm machinery loans. From the Agricultural Finance Databook.

5.4.1 Pseudo Panel Means Across Farm Typologies and Production Types

The means of the model variables are further broken down and listed by farm production type and farm typology in Table 13, Table 14, and Table 15. This is followed by a discussion of the overall summary statistics and differences between farm typologies and production types.

Table 13: Means of Model Variables for Grain Farms by Farm Typology

	Farm typology		
Variable	Resident	Intermediate	Commercial
I	0.0683	0.0693	0.1137
PrIndex	0.705	0.700	0.669
NCFI	0.075	0.145	0.393
DEPR	0.036	0.056	0.098
ACRES	0.00188	0.00254	0.00291
MTR	0.172	0.134	0.233
ENTROPY	0.135	0.181	0.219
WC	0.196	0.318	0.343
IR	0.0695	0.0698	0.0706
OFFI	82.13	40.57	59.45
Number of Observations	158	171	178

Table 14: Means of Model variables for Fruit, Nut, Vegetable, Horticulture and Nursery Farms by Farm Typology

	Farm typology		
Variable	Resident	Intermediate	Commercial
I	0.0311	0.0451	0.0899
PrIndex	0.884	0.886	0.891
NCFI	-0.001	0.064	0.585
DEPR	0.019	0.031	0.101
ACRES	0.00035	0.00042	0.00078
MTR	0.158	0.127	0.246
ENTROPY	0.035	0.050	0.062
WC	0.245	0.284	0.651
IR	0.0717	0.0719	0.0730
OFFI	96.06	52.03	62.87
Number of Observations	179	180	180

Table 15: Means of Model Variables for Livestock Farms by Farm Typology

	Farm typology		
Variable	Resident	Intermediate	Commercial
I	0.0410	0.0491	0.0695
PrIndex	0.786	0.787	0.789
NCFI	-0.004	0.053	0.276
DEPR	0.033	0.043	0.090
ACRES	0.00067	0.00090	0.00060
MTR	0.146	0.117	0.190
ENTROPY	0.117	0.159	0.128
WC	0.127	0.118	0.228
IR	0.0697	0.0700	0.0698
OFFI	78.79	41.17	43.48
Number of Observations	239	252	263

The average rate of investment differs between typologies and commodity enterprises. The average rate of investment is larger for commercial farms compared to resident and intermediate farms and grain farms compared to FNV and livestock farms. Within the sample as a whole, investment expenditures are on average 6.2% of capital stocks. The average investment is 11% for commercial grain farms, 8.9% for commercial FNV farms and 6.6% for commercial livestock farms.

For the sample as a whole, on average, each dollar of capital generated $0.155 of net cash farm income. The range is between -$2.40 to $4.20 in income generated per each unit of capital stock. While most farms earn a modest return on capital, there are some farms that earn extremely low or high returns on capital. Some portion of this is explained by farms which earn very large positive or negative incomes. The rest is due to farms which own very small levels of capital stock and either employ other inputs, are involved in labor intensive activities, or rent these items or services. This low level of capital stock in relationship to net cash farm income results in extreme negative or positive estimates for return on assets.

On average, commercial farms are highly profitable with FNV farms earning the largest return on assets and grain farms earning the lowest return on assets. The average return on assets was 0.39 for commercial grain farms, 0.58 for FNV farms and 0.27 for livestock farms. In contrast, the average return on assets was -0.001 for resident FNV farms and -0.004 for resident livestock farms. These negative estimates are due to average negative net cash farm incomes. It is not uncommon within the ARMS survey data for a large portion of farms to not earn enough from the sale of farm commodities and receipts to cover expenses (Hoppe, 2015). The share of such farms is higher among farms with retired operators, operators having primary occupations other than farming or having annual GCFI less than $100,000. These farms often rely on off-farm income for livelihood and to cover expenses and make investment (Hoppe, 2015).

The average tax depreciation expense as a percent of capital assets is larger for commercial farms compared to resident and intermediate farms. Resident farms had smaller rates of tax depreciation per unit capital assets than intermediate farms. There is a wide degree of variation among these estimates between farms and over the survey period. While the average estimates within typologies are similar to each other and the sample mean of 0.054, the range of the estimates are between 0.00 to 1.24. Part of this variation may be due to differences in annual allowable depreciation tax levels as well as producers adjusting depreciation tax expenses in a given year depending on the level of total farm income to minimize total tax expenditures.

Most farm households are in the middle to upper echelon of US income levels (Hoppe, 2014). According to the US Census Bureau, median U.S. household income in 2013 was $52.25 thousand (Noss, 2014). The average off-farm income level alone (not accounting for farm income) for farms in the ARMS survey was $63.57 thousand. Resident farms, on average, have larger average off-farm income levels compared to resident and intermediate farms and fall within the top echelon of US income levels. The average off-farm income level alone (not including farm income) for resident grain, FNV and livestock farms was $82.13 thousand, $96.06 thousand and $78.79 thousand. Commercial grain and FNV farms had higher off-farm income levels compared to intermediate farms, while the average levels of off-farm income earned by intermediate and commercial livestock farms were similar.

Intermediate farms, on average, are more likely to specialize in fewer crops compared to resident and intermediate farms. On average, commercial farms are most likely to have the greatest degree of diversification. In general, crop farms are more diversified than livestock farms. This may be due to the greater ability to grow multiple grain crops simultaneously within a given year and with fewer additional fixed costs compared to diversifying among different livestock categories. The degree of specialization calculated for FNV crop enterprises is lower than expected. This could be due to the fact that there are many more varieties and types of crops within the single fruit and vegetable categories used to calculate entropy estimates compared to those used for the grain categories. FNV farms may be more diversified among varieties and types of fruits and vegetables than these statistics indicate.

The average number of acres per unit capital is smaller for grain farms compared to FNV and livestock farms. According to MacDonald et al. (2013) larger rates of capital per acre in fruit and vegetable production compared to grain production reflects the higher per unit capital intensive nature of fruit and vegetable production. Across grain and FNV farms, commercial farms employ, on average, less capital per acre land compared to resident and intermediate farms.

In terms of the other variable models, commercial farms had, on average, larger levels of working capital compared to resident farms and intermediate farms. Marginal tax rates, which account for both off-farm and on-farm income, are the largest for commercial farms grain and FNV farms and the lowest for intermediate farms. The output price indexes are fairly similar across farm typologies, as is expected.

5.4.2 Within, Between, and Overall Variance for Pseudo Panel Variables

Table 16 lists the level of within, between and overall variation in the pseudo panel variables. To adequately estimate a fixed effects regression, exogenous variables must exhibit cohort specific variation (Koksal and Wolgenant, 2013). This includes variation within cohorts over time and between cohorts in a given time period. A sample variable that fails to adequately reflect the true population level of variance in both of these dimensions will produce biased estimates. One potential issue in using pseudo panels is that forming panels by taking averages over groups of similar farms may result in a reduction in the level of within variation in the panel data compared to the initial sample population within variation. This could result in small and/or statistically insignificant estimates for these variables.

Table 16: Within, Between and Overall Variance in Pseudo Panel Variables

Variables	Type of Variance	Resident	Intermediate	Commercial
I	Overall	17,769	14,932	54,994
	Between	4,681	10,876	26,008
	Within	16,948	12,864	49,302
K	Overall	117,951	135,361	542,978
	Between	81,034	101,290	327,539
	Within	99,451	109,466	454,594
I/K	Overall	0.0601	0.0491	0.0523
	Between	0.0352	0.0305	0.0291
	Within	0.0522	0.0433	0.0450
PrIndex	Overall	0.1946	0.1910	0.1908
	Between	0.1103	0.1052	0.1030
	Within	0.1624	0.1610	0.1632
NCFI	Overall	0.1463	0.2783	0.2947
	Between	0.0868	0.1090	0.1755
	Within	0.1250	0.2584	0.2398
DEP	Overall	0.0591	0.0370	0.0516
	Between	0.0334	0.0209	0.0307
	Within	0.0522	0.0317	0.0438
Acres	Overall	0.0014	0.0020	0.0036
	Between	0.0009	0.0015	0.0031
	Within	0.0010	0.0014	0.0025
MTR	Overall	0.0609	0.0570	0.0555

Table 16: Continued

	Between	0.0310	0.0251	0.0320
	Between	0.0310	0.0251	0.0320
Entropy	Overall	0.0787	0.0916	0.1059
	Between	0.0541	0.0662	0.0873
	Within	0.0586	0.0654	0.0600
WC	Overall	0.4563	0.3420	0.5220
	Between	0.2414	0.2098	0.3227
	Within	0.4179	0.3010	0.4423
IR	Overall	0.0178	0.0177	0.0179
	Between	0.0071	0.0070	0.0066
	Within	0.0168	0.0168	0.0170
OFFI	Overall	44.8255	30.8884	67.3705
	Between	36.1077	15.2234	28.6644
	Within	38.7398	27.7696	61.0437

There is an adequate level of variation both within cohorts over time and between cohorts in a given time period. In general, the level of variation within cohorts over time is greater than the level of variation between cohorts over time. This is indicative of the cyclical nature of agriculture resulting in large variation in key variables over time.

5.5 Comparing Cross Sectional Survey Data with Pseudo Panel

To make sure that my pseudo panel is reflective of the actual survey data I compare the means, standard deviations, and ranges of the model variables in the survey dataset with those obtained by constructing pseudo panels. As seen in Table 17, the mean values of the variables within each typology for the pseudo panel dataset are almost identical to those of the survey dataset.

Table 17: Means of Variables in Survey and Pseudo Panel Datasets

	Resident		Intermediate		Commercial	
Variable	Survey	Panel	Survey	Panel	Survey	Panel
I	7,706	7,882	13,384	13,735	79,503	74,352
K	196,489	195,267	267,815	274,425	812,031	862,934
I/K	0.0512	0.0435	0.0625	0.0520	0.1147	0.0904
PrIndex	0.7855	0.7898	0.7691	0.7879	0.7813	0.7822

Table 17: Continued

NCFI	-0.0194	0.0084	0.1125	0.0654	0.5735	0.3826
DEP	0.0280	0.0260	0.0501	0.0399	0.1220	0.0956
Acres	0.0025	0.0009	0.0047	0.0015	0.0051	0.0022
MTR	0.1497	0.1570	0.1070	0.1214	0.2087	0.2166
Entropy	0.0870	0.0898	0.1516	0.1294	0.2017	0.1556
WC	0.3547	0.1650	0.4576	0.2155	0.7092	0.4068
IR	0.0673	0.0701	0.0672	0.0702	0.0653	0.0707
OFFI	93.4	87.4	51.7	47.8	53.4	56.5

The similarity between the means across typologies for the two datasets indicates that the cohort observations are representative of the underlying typology variable values in the original survey dataset. By taking means across similar farms, the variables in the pseudo sample dataset have a lower variance than the original observations in the survey dataset. This is demonstrated in Table 18..

Table 18: Standard Errors of Variables in Survey and Pseudo Panel Dataset

	Resident		Intermediate		Commercial	
Variables	Survey	Panel	Survey	Panel	Survey	Panel
I	31,928	17,769	18,724	14,932	108,970	54,994
K	231,964	117,951	315,513	135,361	1,097,405	542,978
I/K	0.2460	0.0601	0.0710	0.0491	0.1209	0.0523
PrIndex	0.2297	0.1946	0.7835	0.1910	0.8073	0.1908
NCFI	4.6567	0.1463	0.1222	0.2783	0.6689	0.2947
DEP	0.2362	0.0591	0.0638	0.0370	0.1292	0.0516
Acres	0.1082	0.0014	0.0062	0.0020	0.0046	0.0036
MTR	0.1097	0.0609	0.1285	0.0570	0.2175	0.0555
Entropy	0.1194	0.0787	0.1636	0.0916	0.1758	0.1059
WC	185.9064	0.4563	10.3295	0.3420	63.1318	0.5220
IR	0.0196	0.0178	0.0686	0.0177	0.0680	0.0179
OFFI	201.9686	44.8255	51.3605	30.8884	56.1405	67.3705

The variance reduction differs across variables and farm typology. The variance of farm capital investment declines across all farm typologies, though only to a small degree for intermediate farms. For resident farms, forming pseudo panels has a larger impact on reducing the variance on the following variables: off-farm income, working capital, acres, and net cash farm income. There is a similarly large reduction in the variance of working capital levels for intermediate and commercial farms, but much less of a reduction in variance across the other farm types for net cash farm income, acres and off-farm income. For intermediate and commercial farms, forming pseudo panels results in a large decrease in the variance interest rates and price index variable across farms. The pseudo panel process leads to a greater reduction in marginal tax rates and depreciation expense measurements for commercial farms compared to other farm typologies. This reduction in variance should take away some of the noise within the survey data and better enable us to identify the actual impacts of changes in variable levels on farm responses to investment.

Table *19*-Table *21* provide the minimum and maximum value as well as the range of observations in the survey dataset and in the pseudo panel dataset by farm typology. In general, taking cohort means greatly reduces the range of most of the variable values. This is because by using averages across similar farms many of the extreme values that occur within the original survey dataset are removed. These extreme values come from both extreme values of the observations themselves and by normalizing by farms having either very large or small levels of capital stocks.

Table 19: Minimum, Maximum and Range for Model Variables for Resident Farms in Survey vs. Pseudo Panel Datasets

	Survey			Panel		
Variable	min	max	range	min	max	range
I	0	2,110,000	2,110,000	0	684,521	684,521
K	-7	6,814,000	6,814,007	90,520	7,374,659	7,284,139
I/K	0.000	24.784	24.784	0.000	0.596	0.596
PrIndex	0.267	1.230	0.963	0.329	1.230	0.901
NCFI	-118.680	775.000	893.680	-0.324	2.622	2.946
DEP	0.000	30.900	30.900	0.002	0.664	0.662
Acres	0.000	15.074	15.074	0.000	0.033	0.033
MTR	0.000	0.396	0.396	0.000	0.396	0.396
Entropy	0.000	0.623	0.623	0.000	0.465	0.465
WC	(25,685)	5,051	30,736	-1.197	8.996	10
IR	0.0356	0.1070	0.0714	0.0366	0.1070	0.0704
OFFI	-178.5	10462.5	10,641	-7.4	1,313.6	1,321

Table 20: Minimum, Maximum and Range for Model Variables for Intermediate Farms in Survey vs. Pseudo Panel Datasets

	Survey			Panel		
Variable	min	max	range	min	max	range
I	0	2,093,850	2,093,850	0	428,149	428,149
K	(7)	13,000,000	13,000,007	0	1,474,600	1,474,600
I/K	0.0000	29.3283	29.3283	0.0000	0.7432	0.7432
PrIndex	0.2673	1.2300	0.9627	0.3348	1.2300	0.8952
NCFI	-602.4971	276.8860	879.3831	-0.9584	1.7545	2.7129
DEP	0.0000	25.9810	25.9810	0.0000	1.2432	1.2432
Acres	0.0000	5.9107	5.9107	0.0000	0.0223	0.0223
MTR	0.0000	0.3960	0.3960	0.0000	0.3960	0.3960
Entropy	0.0000	0.6949	0.6949	0.0000	0.4327	0.4327
WC	-174,597	24,044	198,641	-0.447	8.094	9
IR	0.03560	0.10700	0.07140	0.03661	0.10700	0.07039
OFFI	-45.7	6500.0	6,546	0	498.8	499

Table 21: Minimum, Maximum and Range for Model Variables for Commercial Farms in Survey vs. Pseudo Panel Datasets

	Survey			Panel		
Variable	min	max	range	Min	max	range
I	0	20,600,000	20,600,000	0	229,255	229,255
K	-7	126,000,000	126,000,007	10,030	1,471,601	1,461,571
I/K	0.00	162.27	162.27	0.000	0.474	0.474
PrIndex	0.2673	1.2300	0.9627	0.3287	1.2300	0.9013
NCFI	-369	677	1,046	-2.6284	4.2015	6.8299
DEP	0.0000	45.3983	45.3983	0.0000	0.5490	0.5490
Acres	0.0000	7.0175	7.0175	0.0000	0.0167	0.0167
MTR	0.0000	0.3960	0.3960	0.0000	0.3300	0.3300
Entropy	0.0000	0.6226	0.6226	0.0000	0.4703	0.4703
WC	-1,112,331	116,019	1,228,350	-2	5	6
IR	0.0356	0.1070	0.0714	0.0358	0.1070	0.0712
OFFI	-1,054	13,501	14,555	-13	307	321

Taking the cohort averages has the largest impact on revenue and asset variables such as investment, capital stock, income, depreciation, working capital levels and off-farm income levels. The impact on working capital levels is very staggering, reflecting a large degree of variation between actual working capital levels in the survey population and those across farms by cohort. Unsurprisingly, there is little impact on marginal tax rates, entropy variables, interest rates and price index variables. These variables would tend to have less variation in their absolute level across farms. In addition, the last two are measured using regional vs. farm specific data which already accounts for outliers. The range of acre estimates is reduced by taking farm means, even by taking into account differences in farm sizes. It appears that within farm typologies the acres per unit capital can vary widely.

5.6 Construction of Alternative Pseudo Panel Datasets

The above pseudo panel dataset 1 was one of 8 initial pseudo panel datasets constructed. The other pseudo panels constructed either utilized A) a different number of regions and/or commodity types or B) measures of economic size rather than farm typologies. ARMS divides producers into 48 individual states, 10 farm production regions, 9 ERS farm production regions, or 5 NASS US regions. Farms are classified using 19 commodity types, which can further be aggregated into either 7 or 9 commodity categories. Using these different categories, I explored constructing pseudo panels using the 3 farm typologies as well as 19 commodity types and 10 production regions. I refer to this as panel dataset 2. I use this additional constructed panel to test the robustness of my results obtained using panel dataset 1 to differences in the number of regions and commodity types. Panel dataset 2 provides an unbalanced panel dataset of 6,913 observations total. Unfortunately, the average number of farm observations per cohort mean is only 51 in this dataset. This is below the minimal 100-200 observations for consistent estimators recommended by Verbeek and Ninjam (1992).

Other measures of economic size I explored to create alternative pseudo panels included: A) 4 categories created by the interaction of high and low sales values with high and low asset values giving a measure of household economic well-being, B) 4 farm acre size quartiles, C) 4 asset values quartiles, and D) 5 operator age categories. Each of these was interacted with ERS production regions to differentiate between farms by region. The ERS production regions were chosen as they are constructed to reflect both physical location and differences in production type due to physical location of the farm. Unfortunately, any category including a measure of economic size will not be completely time invariant. Categories involving sales values are most likely to create issues with time invariability while categories involving measures such as age in a base year or acres are more likely to be stable over time. For this reason, age has been used in other pseudo panel studies (Russel and Fraas, 2005; Whitaker, 2009). In addition, age has been found to be correlated with investment and is a significant variable explaining investment behavior when the cross sectional survey dataset is used. Unfortunately, within ARMS the survey question is often left blank by respondents and imputed as 55 when conducting the survey.[12] Utilizing age could result in incorrectly classifying a large number of farms within cohorts and lead to biased estimates of cohort mean values. Given these considerations, from these additional constructed datasets I choose to compare my results using panel dataset 1 to those obtained utilizing the panel dataset formed splitting farms by acre quartiles and ERS regions. This alternative panel dataset is referred to as panel dataset 3. Panel dataset 3 provides a balanced panel dataset with 648 cohort observations.

[12] Source is ARMS training session attended in Summer 2015 at ERS

CHAPTER 6: EMPIRIAL MODEL

6.1 Panel Data Model Using Cohort Mean Observations

Starting with the model in (3) and assuming a linear form, the empirical regression model can be written as follows:

$$I_{c,t} = B_0 + B_1 PrIndex_{c,t} + B_2 NCFI_{c,t} + B_3 NCFI_{c,t}^2 + B_4 OFFI_{c,t} + B_5 IR_{c,t} + B_6 DEP_{c,t} + B_7 Acres_{c,t} + B_8 Entropy_{c,t} + B_9 MTR_{c,t} + B_{10} WC_{c,t} + R_c + I_c + T_t + u_c + e_{c,t} \qquad (4)$$

where the subscript c indicates that the observation is the cohort mean, $R_{c,t}$ and $I_{c,t}$ are cohort dummies for resident and intermediate farms, T_t are individual year dummies, u_c represents time invariant differences in investment across cohorts, and $e_{c,t}$ is the idiosyncratic error term for each cohort at time t. Income is square to reflect the changing impact of an extra dollar of income on investment at different income levels. The regression model in (4) can be written as:

$$I_{c,t} = B_0 + B_k X_{c,t,k} + u_c + e_{c,t} \qquad (5)$$

where $X_{c,t}$ is a vector of cohort means of the k dependent variables in the model and B_k is a vector of coefficient values for each dependent variable in the model.

6.2 Fixed Effects

The pseudo panel regression model developed by Deaton (1985) treated estimated population effects using cohort level observations as measurement error issue. 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 fixed effects estimator assumes that the cohort time invariant differences, u_{ct}, are correlated with the values of the independent variables. If this is the case, then estimating the model using OLS will result in biased estimates. Instead, the data must first be transformed to remove these cohort time invariant differences. One method to transform the data is to take the difference between the observation in time t and the average value of the observation separately by cohort for each variable. This results in the following between estimator model:

$$\ddot{I}_{ct} = B_0 + \mathrm{B}\ddot{x}_{ct} + \ddot{u}_{ct}$$

where $\ddot{I}_{ct} = I_{ct} - (\frac{1}{T}) \sum_{i=1}^{T} I_{ct}$, $\ddot{X}_{ct} = X_{ct} - (\frac{1}{T}) \sum_{i=1}^{T} X_{ct}$; $\ddot{u}_{ct} = u_{ct} - (\frac{1}{T}) \sum_{i=1}^{T} u_{ct}$ (6)

$\ddot{I}_{ct}$, $\ddot{X}_{ct}$, and $\ddot{e}_{ct}$ are the deviation of the cohort observations in time t from their average value over the sample period. The regression above can be estimated using pooled OLS with the standard error corrected for degrees of freedom.

If the cohort unobserved effects are correlated with the regressors, the fixed effects estimated coefficients will be unbiased while estimates using the alternative, a random effects model, will be biased. Downsides of using a fixed effects model include the inability to include time invariant dependent variables and the sensitivity of the estimates to the relative level of between and within variation. This model will be less accurate in estimating marginal impacts of changes in variables that exhibit little relative variation within a given cohort over the time period.

6.2.1 Comparing Fixed and Random Effects Models

If the unobserved effects are not correlated with the regressors, then a fixed effects model will be unbiased but not efficient. In that case, a random effects model would be the appropriate model to use, as it would be both unbiased and the most efficient. The random effects model treats the cohort differences as a random error term and incorporates this into the regression composite error term v_{it}. The random effects model would be:

$$I_{c,t} = B_0 + B_k X_{c,t} + v_{c,t} \ ; \quad \text{where } v_{ct} = u_c + e_{ct} \qquad (7)$$

In practice this is estimated using a weighted combination of the within estimator, which is equivalent a pooled OLS estimator, and the between estimator in the fixed effects model. The random effects model is estimated as follows:

$I_{c,t} - \lambda\bar{I}_c$ = (1-λ)B_0 + ($X_{c,t,k}$- $\lambda\bar{X}_c$)B$_k$ +(1-λ)$u_c + e_{ct}$; where e_{ct} = ((1- λ)v_c + (1-λ)u_{ct}) (8)

λ is a weighted average of the variance of v_i and u_{ct} and referred to as rho. The benefits of a random effects model include that time invariant variables can be included as well as a greater number of degrees of freedom are available without the estimation of the additional fixed effects terms. Both the fixed effects and random effects models assume that the errors are serially uncorrelated across time within cohorts and between cohorts within the same time period.

6.2.2 Heteroscedasticity Robust Hausman Test

The Hausman test examines the validity of imposing these extra orthogonality conditions within the fixed effects regression. The null hypothesis is that both the fixed effects and the random effects are consistent but the random effects model is more efficient. The alternative hypothesis is that only the fixed effects is consistent. The traditional test implemented by most statistical packages requires that the fixed effects and the error terms are homoscedastic and normally distributed. This is most likely not the case given the heteroskedastic nature of the ARMS survey data and farm investment (see section 6.3). Hence, I cannot use the traditional Hausman test. Hence instead I use a heteroscedasticity robust version of the Hausman test based upon Hoechle (2007) and Cameron and Trivedi (2010). According to Hoechle (2007), a Wald test of γ_k =0 for all k variables in the regression model below is equivalent to performing the Hausman test and allowing for heteroscedasticity and autocorrelated error terms. The regression model is as follows:

$$I_{ct} - \lambda\bar{I}_c = (1-\lambda)B_0 + (X_{ct} - \lambda\bar{X}_c)B_k + (X_{ct} - \bar{X}_c)\gamma_k + v_{ct} \quad ; v_{ct} = u_c + e_{ct}$$

$$\text{where} = 1 - \sqrt{\sigma_e^2/(\sigma_u^2 + \sigma_e^2)}\ ; \quad \bar{I}_c = \left(\frac{1}{T}\right)\sum_{i=1}^{T} I_{ct}\ ; \quad \bar{X}_c = \left(\frac{1}{T}\right)\sum_{i=1}^{T} X_{ct} \qquad (9)$$

$\bar{I}_{ct}$ and $\bar{X}_{ct}$ are the cohort mean values over time for the dependent and independent variables, u_c is the cohort fixed effect which has a variance of σ_u^2, and e_{ct} is the idiosyncratic error term which has a variance of σ_e^2.

To perform this test I followed the steps outlined in Hoechle (2007). I first ran a random effects regression of my model assuming homoscedastic errors. Then I calculated λ, $\bar{I}_{ct}$ and $\bar{X}_{ct}$. I next calculated the difference between the variables and the group means times λ for the independent and dependent variables separately. These are the terms $I_{ct} - \lambda\bar{I}_c$ and X_{ct}- $\lambda\bar{X}_c$ in the above model and represent the random effects. Next I calculate the difference between the variables and the group means by cohort. These represent the fixed effects and are the terms X_{ct}- $\bar{X}_c$ in the above model. The model was then re-estimated including both the fixed effects and random effects terms and clustering the standard errors. An F test was performed to see if it was possible to reject the null hypothesis that γ_k =0. This is equivalent to stating that the fixed effects in the model are statistically insignificant from zero. If the null hypothesis that γ_k =0 can be rejected, than one can conclude that significant fixed effects are present in the model. Estimating the model using a random effects model will result in biased coefficient values. If I cannot reject the null, than I can use the random effects model concluding that both the random and fixed effects models are both consistent but the random effects model is more efficient. The results of this test for each of the three commodity types are provided in Table 22.

Table 22: Heteroskedastic Robust Hausman Test Results

	Grain Farms	FNV Farms	Livestock Farms
F-statistic	3.84	4.73	3.46
P-value	0.0002	0.0000	0.0005

Given the above results, I reject the null hypothesis that the fixed effects are statistically insignificant for all three of the estimated regressions. I conclude that there are statistically significant fixed effects present and that the correct model to use is the fixed effects model.

6.2.3 Other Model Forms Explored

Early on I compared using the fixed effects and random effects models with either 1) OLS model with clustered standard errors, 2) a maximum likelihood random effects model, 3) a feasible generalized least square model for panel data allowing for heteroscedasticity between panels and serial autocorrelation within panels, 4) fixed effects model, and 5) a differenced GMM model. The results were similar across the models, with the main differences being that the magnitude of the coefficients decreased and the coefficients were less likely to be statistically significant using a fixed effects model vs. an OLS model.

The maximum likelihood model returned very similar coefficient values as the fixed or random effects models with the main difference being the significance of the coefficients, which were higher under the maximum likelihood model. While this model was promising in that it allows for heteroskedastic and correlated errors, it rests on the assumption that the errors are normally distributed. In graphing my errors, I find that even after normalizing by capital stock levels and taking averages across pseudo panels the errors appear normally distributed except for at the tail ends of the distribution. On the whole I cannot guarantee that I have normally distributed errors. For this reason and given my rejection of the random effects model in general, I do not report the maximum likelihood results.

The generalized least squares model also returned similar results in terms of the signs of the coefficients as the fixed effects model and an OLS model with clustered standard errors, though the coefficients were more likely to be significant and the magnitude of the coefficients slightly larger under this model compared to the fixed effects model. The results under this model (which was tested initially before I choose to use interaction terms and allow for different coefficients across farm typologies) returned similar results to those obtained by running a survey reg model in the cross section. Given that I find evidence of fixed effects, the generalized least squares model was rejected in favor of a fixed effects model.

I also explored using a first difference model instead of a between estimator to remove the fixed effects. Using a first differenced model, the fixed effects are removed in this case by taking differences between variable values over subsequent periods. This model would be preferred if the fixed effects are related to differences in the levels of variables between subsequent periods vs. the average level of the variables over the sample period. The model assumes that changes in the error terms across time are uncorrelated with the changes in the independent variables. This is a weaker form of erogeneity compared to the between estimator, which assumes that the level of the errors is uncorrelated with the level of the independent variables. This method corrects for potential unit root behavior and rules out spurious regressions. Using a first difference estimator requires that the change in the level of the variables between subsequent time periods exhibits variation, both within and between cohorts, and assumes that changes in the error term between periods are serially uncorrelated. The results obtained using the first difference estimator were similar to the fixed effects model, though the overall coefficient values and significance levels were different. My choice to use the fixed effects model vs. a first difference model was based on the belief that differences in farm investment across time periods, production type, and farm typology are more likely to be related to differences in the average level of model variables vs. to changes in these variables between time periods.

The final model I attempted to use was the Arellano-Bond estimator. This is a differenced GMM model for fixed effects equations which include lagged dependent variables. This model is commonly used in the business finance and agricultural economics literature. It addresses the fact that with the inclusion of a lagged dependent variable the between estimator to control for fixed effects is no longer valid. Taking the difference between variable levels and the mean each period leads to correlation between the average value of the error term and the lagged dependent variable. To correct for this, the model uses the difference (as well as levels in the system version of the model) of past lags of independent variables as instrumental variables. I attempted to use this model but found that the resulting signs for my coefficients were largely insignificant and/or did not conform to economic theory. This leads me to conclude that the lagged differences of the independent variables and of lagged investment are poor instruments for changes in the level of the variables in the current periods. Given the poor model results and overall lack of statistical significance for the lagged dependent variable this model is rejected in favor of the fixed effects model where time dummies are used to capture differences in adjustment behavior over time.

While I would like to conclude that the insignificance of the lagged dependent variable in my model supports the idea that agricultural investment adjusts relatively quickly over time, given the overall results of this model I cannot reject either of the following two opposite conclusions. The first is that my results are due to the use of pseudo panels. Taking averages over different cohort samples each period may weaken the ability to identify links between current and lagged variables and hence the ability to link farm investment behavior over time.

While this does not mean that it is not beneficial to use pseudo panels, it does mean that certain variables, such as changes in incomes, may be easier to link across cohort samples over time compared to lagged values of variable and that identifying adjustment behavior may be more difficult. The second alternative conclusion is that my results are due to the use of initial survey data which does not account for disinvestment. In theory a producer could be a net seller of farm capital in a given period. The survey data only records zero investment or positive investment levels. Creating pseudo panels from such data could further limit the ability to capture error adjustment behavior over time.

6.3 Heteroscedasticity and Autocorrelation

I suspect that heteroscedasticity will be an issue in my model. Heteroscedasticity arises in cross sectional datasets where the scale of the dependent variable and its explanatory power differs across observations (Woodridge, 2005, p.191). A large portion of the heterogeneity within the constructed pseudo panels is due to the nature of the ARMS cross-sectional data. Farm financial measurements differ widely between farms across different size and production type categories. These differences lead to large standard errors and inflate the residual estimates when estimating within the cross-sectional dataset. Creating the pseudo panel data by clustering farms on similar characteristics further magnifies these differences. In addition, equipment, machinery and structures are bought in discrete vs. continuous units. This creates a greater degree of variance between different size investments than otherwise would be seen.

Panel datasets may suffer from both heteroscedasticity and autocorrelation. Differences in sample means linked to cohort difference and differences in sample measurement error between different cross sections over time could lead to heteroscedasticity between panel estimates within the same time period or autocorrelation between error terms within cohorts over time. The latter is referred to as group-wise heteroscedasticity. These differences could also lead to contemporaneous serial correlation, which consists of homoscedasticity within certain cohort groupings but heteroscedasticity between these distinct groups of cohorts within a single time period.

Forming cohorts in which the number of cross-sectional observations used to construct the cohort mean differs, either between cohorts in the same time period or in same cohort over multiple time periods could introduce heteroscedasticity, even if the initial cross sectional dataset was homoscedastic (Koksal and Wohlgenant, 2011). This is an issue in my pseudo panel dataset. The number of available cross sectional observations within the ARMS dataset varies over time. The portion of farms sampled each year within the categories used to construct pseudo panels, farm production type and region, also varies by year in the ARMS. Within the ARMS survey weights are used to correct for this when compiling population estimates.

If heteroscedasticity and/or autocorrelation is present the fixed and random effects coefficient estimates will still be unbiased, consistent and asymptotically normally distributed, but the standard errors and tests statistics may be biased. Weighting each cohort estimate by the square root of the number of cohort observations is one means in which previous studies have addressed this issue (Koksal and Wolgenant, 2013). Instead, I rely on the ARMS weights when constructing my cohort means and use heteroscedasticity robust estimation methods to solve this issue.

6.4 Clustering Standard Errors

To address the heteroscedasticity and autocorrelation present in the standard errors, I choose to cluster the standard errors across cohorts. This corrects for heteroscedasticity between cohort error terms in a given time period and correlation between errors terms within cohorts over time. Clustering standard errors when using ARMS survey data takes advantage of the stratified nature of the survey process as well as reduce the variance of estimates when the clustering categories are representative of the survey design (Weber and Clay, 2013). My clustering categories, commodity type, region, and typology, are representative of the ARMS survey sampling categories of region, farm size and commodity type. The only assumption made when clustering errors is that no contemporaneous serial correlation exists. To address this potential, the model was re-estimated using a technique that takes into account serial correlation. The estimates were unchanged compared to using the fixed effects model and clustering standard errors on cohorts.

6.5 Checking for Multicollinearity

When I was initially working with the survey data and choosing the variables to include in my model I carefully checked for multicollinearity by first comparing the correlation coefficient matrixes and testing for the presence of multicollinearity using the STATA VIF[13] command after running the regressions. These results informed my choice of model variables.

These tests also led to the exclusion of certain expense category variables that while highly correlated to investment were also highly correlated with farm revenues/income measurements.

Table *23* 23 provides the correlation coefficients between revenues and expenditures on different items with both investment, measured as the total level of investment as well as the rate of investment for the survey data in columns 1 and 2 and for the pseudo panel dataset in columns 4 and 5. This is contrasted with the correlation coefficients between revenues and these same expense categories for the survey data in column 3 and the pseudo panel dataset in column 6. This points out that while certain key expense categories are correlated with investment they are also, or to a greater degree, correlated with farm sales/income levels.

Table 23: Pseudo Panel and Survey Dataset Correlation Coefficients Between Investment, Revenues and Expense Category Variables

	cross section			pseudo panel		
Variable	With the level of investment	With the rate of investment	With Sales	With the level of investment	With the rate of investment	With Sales
Value Product	0.36	0.11		0.65	0.32	
Expense Categories:						
Substitutes	0.25	0.03	0.53	0.47	0.23	0.51
Fuel and Repair	0.44	0.04	0.66	0.69	0.37	0.66
Cash Rent	0.32	0.04	0.69	0.55	0.39	0.46
Labor	0.32	0.04	0.49	0.50	0.24	0.64
Interest payments	0.31	0.04	0.34	0.58	0.20	0.41
Depreciation	0.39	0.07	0.30	0.67	0.41	0.59

[13] This measures the variance inflation factor (VIF) or the degree that each variable can be expressed as a linear combination of the other model variables.

One would like to explore the impact of changes in expense categories such as labor, repairs, and interest payments these items on the demand for farm machinery though. Changes in these could, according to neoclassical theory, results in different choices for the optimal level of capital stock and investment demand. Unfortunately, due to the high degree of multicollinearity between these variables and investment, including both in a regression may lead to inaccurate coefficient estimates. Given the importance of changes in either farm income and/or sales on investment it would be problematic to not include this variable. This reasoning prompted my decision to use net cash farm income instead of using revenue and other expense category variables. Unfortunately, while the impact of changes in these categories are accounted for, this formulation imposes limitations in my ability to directly link changes in investment with changes in specific expense categories.

6.6 Allowing Coefficients to Differ by Farm Typology

To capture differences in investment across farm typologies due to differences in either prices, cash flow measurements, or tax variables I include interaction terms between resident and intermediate farms and the following variables: output prices, income, income squared, depreciation, tax rates, and liquidity. A single coefficient across all farm typologies is assumed for the remaining variables: off farm income, acres, entropy, and interest rates.

6.6.1 T-Test for Differences in Coefficients by Farm Typology Across Other Coefficients

This technique allows me to include the different typologies within my regression, increasing the within variation present among farms but also account for differences in marginal impacts according to farm typologies while not allowing all the variables to differ conserves degrees of freedom. Unfortunately, this assumes that the marginal impacts of the remaining variables are similar across farm typologies. To test this assumption, I ran the regressions including interaction terms for all of the variables and tested each variable in the model to see if

I could reject the null hypothesis that the coefficient on the interaction terms for resident and commercial farms are both equal to zero. The results of this test are provided in Table 24.

Table 24: Pseudo Panel Fixed Effects Regression Test Results for Differences in All Coefficient Values Across Farm Typologies

Variable	Grain Farms		FNV Farms		Livestock Farms	
	F-Statistic	p-value	F-Statistic	p-value	F-Statistic	p-value
PrIndex	1.69	0.19	3.77	0.02	0.07	0.92
NCFI	6.81	0.00	7.01	0.00	2.96	0.06
$NCFI^2$	3.78	0.03	2.86	0.06	1.69	0.19
DEP	1.27	0.29	1.55	0.22	1.17	0.31
Acres	3.24	0.04	1.12	0.33	1.91	0.15
Entropy	0.63	0.53	0.89	0.41	0.19	0.82
MTR	5.99	0.00	2.44	0.09	1.94	0.15
WC	0.13	0.87	2.14	0.12	0.36	0.70
IR	0.70	0.50	1.24	0.29	0.57	0.56

The null hypothesis is that the coefficient value of the variable times an interaction term for resident farm and the coefficient on the variable times an interaction term for intermediate farms are both statistically insignificant from zero. Separate regressions were performed for grain farms, FNV farms, and livestock farms.

The results of this test confirm both the overall findings of my study, that there are marked differences between investment in response to changes in incomes across farms as well as due to changes in tax rates and prices within certain commodity groups. In terms of the other variables that I do not allow to differ by farm typology, except for acres for grain farms, I am unable to reject the null that the coefficient values differ between farm typologies for these variables. This further lends credence to my choice of coefficients to vary across farm types and my results in later sections.

6.7 Separate Regressions for Different Production Types

I estimate the regressions separately for grain[14], FVP[15] and livestock enterprises[16]. This allows me to compare differences in coefficient values due to differences in investment behavior across these different types of production systems. For livestock farms, I compare estimating the regressions including breeding livestock investment with the results when breeding livestock is omitted from investment. In addition, I estimate the model for dairy and poultry farms separately.

6.8 Calculating Partial Investment Elasticities

For the ease of explanation and for use later on, I calculate partial investment elasticities for the key variables in the model: output prices, net farm income, depreciation tax expenses, marginal tax rates, working capital and interest rates. The partial investment elasticities indicate the average annual change in dollars invested in capital per a 1% change in value of the independent variable. To obtain these estimates I divide the STATA partial elasticities, which are the model coefficients multiplied by the average of the independent variable for each farm typology group over the sample period, divide by 100 and multiply by the average level of farm capital for the corresponding farm typology group over the 1996-2013 time period.

6.9 Additional Variables Employed to Measure Credit and Financial Constraints

Instead of working capital, other studies have utilized variables such as debt, net worth, and the debt to asset ratio to examine the impact of financial and credit constraints on farm investment. To further test the impact of financial constraints on intermediate farms, I explored using these other measures instead of working capital. I re-estimated the regressions separately

---

[14] Grain farms include general cash grains, wheat, corn, soybean, sorghum, rice, and tobacco and cotton farms. These correspond to farms in the "cash grain" and "cotton and tobacco" but not the "other crops" commodity group category.

[15] FNV farms include farms in the "fruits, nuts, and vegetables" and "nursery and greenhouse" commodity type categories

[16] Livestock farms include farms in the "beef, hog and sheep", "dairy" and "poultry" but not the "other livestock" commodity type categories.

replacing the variable working capital with first total farm debt, then net worth, and finally the debt to asset ratio. To control for the impact on investment in the current period on the level of farm debt and assets, I use lagged values for debt, net worth, and the debt to asset ratio. Total farm debt and net worth levels were normalized by the total farm level of capital stocks.

6.10 Notes on Other Independent Variables Explored

In addition to the variables used in the model, during the course of completing this dissertation I looked at including other variables to further explain farm investment. These included 1) other assets such as farmland and breeding livestock as independent variables, 2) sales over multiple time periods, 3) and lagged capital asset levels. Farmland or breeding livestock could serve as either complements or substitutes to other forms of farm capital investment. In the first case, the purchase of additional farmland or livestock would require addition investment in machinery, equipment, or structures such as crop storage or livestock housing. In the latter case, given a fixed amount of available dollars to invest, the producer makes a choice between investment within each category depending on the relative price and returns.

To explore the impact of farmland and breeding livestock investment on machinery, equipment, and structural investment, I constructed variables representing the annual cohort average of the following: asset values, dollars of investment expenditures, the percent of farms making a positive expenditure. These variables were added as independent variables to the regression equation. This was done separately for each variable and for farmland and breeding livestock. In general, I find no statistically significant impacts or improvement in goodness of fit from inclusion of these variables within the regression.

Assuming farms only look at current income levels when making investment decisions assumes naive investment behavior. Instead farms may take into account prices received or quantities sold over multiple prior time periods when making investment decisions. I constructed 2 different variables to test the assumption of naïve investment behavior. The first variable constructed is the difference in the average value of cohort revenues between the current and prior year. This variable is statistically insignificant when included in the regression and does not improve the goodness of fit of the regressions. The second variable created is the average value of net cash farm income over the current year and the past two years. The result when included in the regression was smaller estimated coefficient values and a slight reduction in the goodness of fit statistics for grain and FNV farms and a slight increase in the coefficient values and goodness of fit statistics for livestock farms.

I would expect to obtain a negative coefficient value on an independent variable for the value of capital stocks in the prior period. This assumes that an increase in average cohort investment in the prior period triggers a reduction in investment this period. When I include this variable in my regressions I consistently obtain negative signs on the coefficient across farm typologies, indicating a link between greater investment last period and lower investment this period. Unfortunately, none of the coefficients were statistically significant within the various regressions.

6.11 Comparing my Results with the Cross Section and Other Panels

I estimate the regressions for the cross section and for panels 2 and 3. This provides a check on the sensitivity of my results to the use of pseudo panels in general and the specific choice of categories used to construct the pseudo panels. The regressions are estimated for the pseudo panel dataset using an OLS regression with jackknifed standard errors and applying the ARMS weights. The method used for panel 2 is the same as that of panel 1. When estimating the regressions for panel 3, instead of using dummy variables for resident and intermediate farm typologies times the coefficient values, I instead multiply the coefficient value times a variable specifying the percentage of resident and intermediate farms within the cohort.

6.12 Specifying Three Hypothesis

I use the above model to test three main hypotheses regarding differences in the rate of farm capital investment between typologies given equivalent changes in key model variables. The hypotheses are: 1) commercial farm investment rates will increase to a greater degree given increases in output prices and the returns to investment, 2) resident farms increase investment rates more given favorable changes in tax policy variables, and 3) intermediate farm investment rates increase to a greater degree given decreases in the level of credit and financial constraints. These hypotheses are related to previous literature findings that farm size investment differs by farm size measurement (Ariayante and Featherstone, 2009; Barry et. al., 2000; Bierlen and Featherstone, 1998) where farm size could be defined by sales value, income level, number of acres, or livestock units. In particular, hypothesis two tests the common literature finding that small farms are more responsive to changes in cash flow measurements (Ariayante and Featherstone, 2009; Barry et. al., 2000; Bierlen and Featherstone, 1998), hypothesis one the assertion that farms with higher off-farm incomes will be more responsive to changes in tax policy (Durst, 2009; Hoppe and MacDonald, 2013), and hypothesis one that larger farms are more responsive to changes in sales levels. By using the farm typologies, I link differences in farm occupation type with differences in off-farm income levels. This allows the difference in primary occupation, rather than just differences in off-farm income levels, to explain differences in investment rates given differences in farm typologies. Finally, all three hypotheses allow me to either reject or verify the statistical significance of key differences I see within farm typologies regarding the impacts of different variables on farm capital investment.

6.12.1 Hypothesis 1

Hypothesis one flows from hypothesis two and three as well as the nature of commercial farming. Commercial farms generally highly profitable (Hoppe and MacDonald, 2013), operate on a large scale, and may face tight profit margins. They generally have positive return on asset and operating profit margins, compared to small farms where the median farm operating profit and rate of return on asset is negative and fall within the critical zone (Hoppe and MacDonald, 2013). Part of this may be explained by the fact that for many resident farms, the profitability of the farm may be secondary to other reasons to farm such as lifestyle choices (MacDonald et al., 2014). These resident farms rely on outside farm income to supplement farm income and invest (MacDonald et al., 2014). For other small farms, credit and financial constraints may be a greater issue. Compared to these farms, commercial farms will have a greater ability to take advantage of positive investment opportunities and expand production given increases in output prices or the returns to investment. Additionally, the measure of the returns to investment utilizes net cash farm income, which includes government payment and other income from farming activities. Moderate, mid-sized and large-scale family farms are more likely to receive government payments than smaller farms (Hoppe, 2014). The overall level of NCFI earned by commercial farms is, on average, significantly larger for commercial farms compared to intermediate farms. Due to these factors, I would expect the rate of commercial farm investment to increase more given a change in output prices and/or the returns to investment.

6.12.2 Hypothesis 2

Hypotheses two is based upon the fact that resident farms on average have higher levels of off-farm income compared to intermediate farms and earn a greater share of their income from off-farm activities as compared to commercial farms. For the majority of farms, income taxes are calculated based upon total household income levels, or the sum of off-farm and farm incomes after determining other deductions. Increases in tax depreciation expenses taken, either due to an increase in the allowable tax depreciation rate or an increase in total investment expenditures that period, decreases total farm income and as a result total household income levels. The benefit from such a deduction should be greater for farms earning higher off-farm incomes. An increase in the marginal tax rate should also provide a greater incentive for farms with higher off-farm incomes to invest in farm capital and thus decrease total household income levels. As a result, I hypothesize that an increase in the marginal tax rate or tax depreciation expense rate will result in a larger increase in investment rates for resident farms compared to resident and/or intermediate farms.

6.12.3 Hypothesis 3

Hypotheses three draws upon the theory of credit constraints or imperfect financial markets. The idea is that intermediate farms, having lower levels of farm income compared to commercial farms and lower levels of average off-farm income compared to resident farms, are more likely to be credit constrained. Credit constraints can come from external or internal sources. Credit constrained farms face external credit constraints if the available level of external credit is less than the optimal level of credit they would like to obtain or if there are increasing costs to obtaining external credit. Internal credit constraints may arise if there are reasons why the farm operator declines to take on additional debt given they are below the farm specific theoretical optimal level of debt financing. In these instances, internal sources of financing become preferred over external sources. Additionally, asset and debt levels also become significant in determining investment responses in light of profitable opportunities. A higher level of debt may reduce available levels of financing or lead to higher costs for additional external financing. Higher levels of assets and equity does the opposite. As a results of these forces, investment expenditures are expected to increase to a greater degree given increases in internal funds for credit constrained farms. If lower levels of both off and on-farm income result in greater credit constraints for intermediate farms, I hypothesize that intermediate farm investment rates will increase more given an increase in liquidity, debt and/or equity levels.

CHAPTER 7: REGRESSION RESULTS AND PARTIAL INVESTMENT ELASTICITY ESTIMATES

Within this section I provide the regression results and a summary of the resulting values obtained in other U.S. farm investment panel data studies for similar variables. I also provide the mean and confidence intervals for the calculated partial investment elasticities. This is done for the original model, for a model replacing the working capital variable with different measures of farm financial constraints, and finally for the other pseudo panels constructed.

7.1 Regression Results

The results of two separate regressions are provided in Table 25-Table 30 for each farm production type. The first column indicates the value and t-statistic for coefficients of key variables in the first regression, where I constrain this to be equal across all farm typologies. The second through fourth columns indicate the coefficient values and t-statistics for key variables in the second regression where I allow the coefficient values to differ across farm typologies using interaction terms. I also provide information for each regression on the number of cohort observations, the R^2 statistic and the root mean squared error (RMSE). The resulting values for the time dummy coefficients included in the regressions are provided separately in Table 31 and Table 32. Table 33 provides results for an f-test of the joint significance of the time dummy variables in each regression.

Table 25: Pseudo Panel[1] Fixed Effects Regression Results for Grain[2] Farm Investment 1996-2013

		By Farm Typology		
Variable Name	Single Coef.[3]	Commercial	Resident[4]	Intermediate[4]
PrIndex	0.0303	0.045*	-0.0037	-0.062**
	(1.96)	(2.61)	(-0.13)	(-2.76)
NCFI	-0.0356	0.117*	-0.167	-0.155**
	(-1.01)	(2.27)	(-0.92)	(-3.08)
$NCFI^2$	0.00759	- 0.043*	0.075	0.054*
	(0.90)	(-2.08)	(0.34)	(2.50)
DEP	0.289	0.0274	0.714	0.234
	(1.65)	(0.26)	(1.22)	(1.09)
OFFI	0.000064	0.000078		
	(1.05)	(1.36)		
Acres	4.341	1.577		
	(1.85)	(0.49)		
Entropy	0.0402	0.0316		
	(0.45)	(0.32)		
MTR	0.0803	-0.329*	0.462**	0.400**
	(0.80)	(-2.34)	(3.05)	(2.98)
WC	-0.00690	-0.0065	-0.0012	-0.00006
	(-0.56)	(-0.34)	(-0.04)	(-0.00)
IR	-0.545	-0.540		
	(-0.97)	(-0.91)		
Intermediate	-0.0312*	-0.0635*		
	(-2.59)	(-2.05)		
Resident	0.0266	-0.133***		
	(-1.52)	(-3.59)		
Constant	0.0409	0.115		
	(0.66)	(1.63)		
Observations	507	507		
RMSE	0.0537	0.0527		
R^2	0.218	0.264		

Top number is the coefficient, below in parenthesis is the t-statistic. ***=99%, **=95% *=90% Confidence intervals.

The dependent variable is investment in machinery, equipment and structures divided by the value of farm assets. Farm assets include machinery, equipment and buildings.

[1]Psuedo panel dataset 1 constructed from ARMS survey data. Farms are grouped into cohorts based upon 5 US regions, 9 commodity types, and 3 farm typologies. Standard errors are clustered by cohort. See table A15 for the values of the included year dummy variables.

[2]This regression includes cohorts which fall into the commodity type: 1) cash grains and 2) tobacco and cotton farms. This does not include other crop farms.

[3] In this case a single coefficient is estimated for resident, intermediate and commercial farms

[4] these are the difference from commercial farms

Table 26: Pseudo Panel[1] Fixed Effects Regression Results for FNV[2] Farm Investment 1996-2013

		By Farm Typology		
Variable Name	Single Coef.[3]	Commercial	Resident[4]	Intermediate[4]
PrIndex	0.00079	-0.0412	0.0899*	0.0122
	(0.02)	(-0.66)	(1.86)	(0.23)
NCFI	0.0327	0.128***	-0.115**	-0.255**
	(1.78)	(4.20)	(-3.47)	(-2.92)
$NCFI^2$	-0.0082	-0.052**	0.0535	0.386*
	(-0.72)	(-2.78)	(1.68)	(2.02)
DEP	0.108	0.0062	0.348	0.315
	(1.08)	(0.07)	(1.71)	(1.39)
OFFI	0.00000389	-0.0000526		
	(0.06)	(-0.74)		
Acres	0.437	-1.259		
	(0.12)	(-0.35)		
Entropy	-0.0497	-0.0560		
	(-0.90)	(-1.07)		
MTR	-0.0765	-0.146	0.0743	0.207
	(-1.51)	(-1.46)	(0.66)	(1.68)
WC	0.0050	-0.0016	0.0020	0.0247*
	(0.82)	(-0.39)	(0.34)	(2.49)
IR	0.0222	-0.121		
	(0.05)	(-0.30)		
Intermediate	-0.00434	0.0169		
	(-0.42)	(0.28)		
Resident	-0.00434	-0.00886		
	(-1.09)	(-0.16)		
Constant	0.0729	0.124		
	(1.49)	(1.73)		
Observations	539	539		
RMSE	0.0446	0.0434		
R^2	0.207	0.266		

Top number is the coefficient, below in parenthesis is the t-statistic.

Robust Standard errors clustered by cohort are used. See table A15 for the values of the included year dummy variables.

The dependent variable is investment in machinery, equipment and structures divided by the value of farm assets. Farm assets include machinery, equipment and buildings.

***=99%, **=95% *=90% Confidence intervals.

[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.

[2]This regression includes cohorts where the commodity category is defined as fruit, nut, vegetable, horticulture and nursery farms. These are farms which fall into the commodity type categories: 1) fruit, nut and vegetable and 2) nursery and horticulture farms.

[3] In this case a single coefficient is estimated for resident, intermediate and commercial farms

[4] these are the difference from commercial farms

Table 27: Pseudo Panel[1] Fixed Effects Regression Results for Livestock[2] (not including Breeding Livestock) Farm Investment 1996-2013

		By Farm Typology		
Variable Name	Single Coef[3]	Commercial	Resident[4]	Intermediate[4]
PrIndex	0.0303	0.0442	-0.0284	-0.0181
	(0.83)	(1.24)	(-0.75)	(-0.52)
NCFI	0.0049	0.0702	-0.107	-0.0311
	(0.25)	(1.59)	(-1.92)	(-0.62)
$NCFI^2$	-0.0119	-0.0444	-0.0381	0.0708*
	(-1.11)	(-1.81)	(-0.57)	(2.32)
DEP	0.261**	0.190*	0.267	-0.121
	(3.06)	(2.52)	(1.54)	(-0.93)
OFFI	0.0000018	0.000011		
	(0.05)	(0.21)		
Acres	-3.751**	-4.871*		
	(-2.73)	(-2.57)		
Entropy	0.0218	0.0203		
	(0.93)	(0.80)		
MTR	-0.0421	-0.0267	-0.0147	-0.0601
	(-1.06)	(-0.35)	(-0.16)	(-0.58)
WC	0.0077	0.0090	-0.0052	0.00046
	(1.18)	(0.96)	(-0.53)	(0.02)
IR	0.287	0.412		
	(0.65)	(1.00)		
Intermediate	-0.0079	0.028		
	(-1.07)	(0.66)		
Resident	-0.0100	0.0198		
	(-1.06)	(0.53)		
Constant	0.0115	-0.0207		
	(0.22)	(-0.39)		
Observations	752	752		
RMSE	0.0534	0.0529		
R^2	0.143	0.174		

Top number is the coefficient, below in parenthesis is the t-statistic.

Robust Standard errors clustered by cohort are used. See table A15 for the values of the included year dummy variables.

The dependent variable is investment in machinery, equipment and structures divided by the value of farm assets. Farm assets include machinery, equipment and buildings. Breeding livestock is not included in either investment or farm assets.

***=99%, **=95% *=90% Confidence intervals.

[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.

[2]This regression includes cohorts where the commodity category is: 1) beef, hog and sheep, 2) dairy, and 3) poultry.

[3] when a single coefficient is estimated for resident, intermediate and commercial farms

[4]these are the difference from commercial farms

Table 28: Pseudo Panel[1] Fixed Effects Regression Results for Livestock[2] (including Breeding Livestock) Farm Investment 1996-2013

Variable Name	Single Coef.[3]	By Farm Typology Commercial	Resident[4]	Intermediate[4]
PrIndex	0.0401	0.0611	-0.0518	-0.0508
	(1.02)	(1.37)	(-1.00)	(-1.39)
NCFI	0.00309	0.0644	-0.121**	-0.0826
	(0.17)	(1.73)	(-2.76)	(-1.77)
$NCFI^2$	0.00160	-0.00902	0.0889***	-0.00883
	(0.11)	(-0.58)	(3.51)	(-0.24)
DEP	0.378***	1.97	0.234*	0.212
	(8.59)	(2.52)	(2.22)	(0.84)
OFFI	0.0000018	0.000011		
	(0.05)	(0.21)		
Acres	7.756	3.532		
	(1.80)	(0.76)		
Entropy	-0.0699	-0.0502		
	(-1.61)	(-1.10)		
MTR	0.0306	-0.104	0.202	0.103
	(0.60)	(-0.93)	(1.98)	(0.59)
WC	0.0420	100.2	-102.4	-94.56
	(0.07)	(0.94)	(-0.96)	(-0.89)
IR	0.742	0.501		
	(1.06)	(0.75)		
Intermediate	-0.0079	0.028		
	(-1.07)	(0.66)		
Resident	-0.0100	0.0198		
	(-1.06)	(0.53)		
Constant	-0.0678	-0.0363		
	(-0.95)	(-0.46)		
Observations	752	752		
RMSE	0.0895	0.0874		
R^2	0.448	0.483		

Top number is the coefficient, below in parenthesis is the t-statistic.

Robust Standard errors clustered by cohort are used. See table A15 for the values of the included year dummy variables.

The dependent variable is investment in machinery, equipment, structures and breeding livestock per capital stock. Capital stock is the value of machinery, equipment, structures, and breeding livestock.

***=99%, **=95% *=90% Confidence intervals.

[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.

[2] This regression includes cohorts where the commodity category is: 1) beef, hog and sheep, 2) dairy, and 3) poultry.

[3] when a single coefficient is estimated for resident, intermediate and commercial farms

[4] these are the difference from commercial farms

Table 29: Pseudo Panel[1] Fixed Effects Regression Results for Dairy[2] Farm Investment 1996-2013

		By Farm Typology		
Variable Name	Single Coef[3]	Commercial	Resident[4]	Intermediate[4]
PrIndex			0.060	-0.0239
			(1.54)	(-0.45)
NCFI	-0.0363	-0.0934*	0.00706	0.330**
	(-1.04)	(-2.27)	(0.08)	(3.08)
$NCFI^2$	0.0186	0.0620*	0.133	-0.220
	(1.11)	(2.48)	(0.59)	(-0.97)
DEP	0.328	0.0194	1.020*	-0.261
	(1.65)	(0.07)	(2.25)	(-0.65)
OFFI	0.0000461	0.0000557		
	(0.35)	(0.45)		
Acres	-3.326	-5.907		
	(-1.46)	(-1.11)		
Entropy	0.0352	0.00886		
	(0.43)	(0.10)		
MTR	-0.0295	0.0947	0.000965	-0.422*
	(-0.29)	(0.85)	(0.01)	(-2.44)
WC	-0.0159	-0.0317	-0.0146	0.0470
	(-0.86)	(-0.52)	(-0.18)	(0.78)
IR	0.442	0.796		
	(0.41)	(0.74)		
Intermediate	-0.00585	-0.0942		
	(-0.87)	(-1.70)		
Resident	-0.00715	0.0558		
	(-1.49)	(0.74)		
Constant	0.0591	0.0425		
	(0.63)	(0.41)		
Observations	260	260		
RMSE	0.0602	0.0595		
R^2	0.134	0.199		

Top number is the coefficient, below in parenthesis is the t-statistic.
Robust Standard errors clustered by cohort are used. See table A18 for the values of the included year dummy variables.
The dependent variable is investment in machinery, equipment and structures per capital stock.
***=99%, **=95% *=90% Confidence intervals.
[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.
[2]This regression includes cohorts where the commodity type category is dairy.
[3] when a single coefficient is estimated for resident, intermediate and commercial farms
[4] these are the difference from commercial farms

Table 30: Pseudo Panel[1] Fixed Effects Regression Results for Poultry[2] Farm Investment 1996-2013

			By Farm Typology	
Variable Name	Single Coef[3]	Commercial	Resident[4]	Intermediate[4]
PrIndex			0.00843	0.0389
			(0.11)	(0.77)
NCFI	0.0444	0.0723	-0.0323	0.0667
	(0.74)	(0.47)	(-0.22)	(0.37)
$NCFI^2$	-0.130**	-0.0414	-0.142	-0.291
	(-3.47)	(-0.22)	(-0.74)	(-1.34)
DEP	0.425**	-0.0623	0.631**	0.437*
	(3.38)	(-0.44)	(3.47)	(2.39)
OFFI	-0.0000009	-0.00000246		
	(-0.01)	(-0.06)		
Acres	4.138	0.408		
	(-1.46)	(-1.11)		
Entropy	-0.0833	-0.0673		
	(-1.16)	(-0.85)		
MTR	-0.114	-0.0578	-0.0525	-0.137
	(-1.06)	(-0.29)	(-0.25)	(-0.66)
WC	0.00554	0.0826	-0.0748	-0.159*
	(1.34)	(1.80)	(-1.59)	(-2.66)
IR	-0.238	-0.649		
	(-0.22)	(-0.50)		
Intermediate	-0.00656	-0.00759		
	(-0.61)	(-0.09)		
Resident	0.0205	-0.028		
	(1.00)	(-0.47)		
Constant	0.0443	0.0890		
	(0.42)	(0.69)		
Observations	244	244		
RMSE	0.0388	0.0362		
R^2	0.473	0.567		

Top number is the coefficient, below in parenthesis is the t-statistic.

Robust Standard errors clustered by cohort are used. See table A18 for the values of the included year dummy variables.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.

[2]This regression includes cohorts where the commodity type category is poultry.

[3] when a single coefficient is estimated for resident, intermediate and commercial farms

[4] these are the difference from commercial farms

Table 31: Value of Year Dummies from Pseudo Panel Fixed Effects Regressions by Farm Type 1996-2013

Year	Grain Farms		FNV Farms		Livestock Farms[1]		Livestock Farms[2]	
	All Farms	By Typology	All Farms	By Typology	All Farms	By Typology	All Farms	By Typology
1997	0.0531*	0.0613**	0.0125	0.0112	0.0062	0.0062	-0.002	0.0009
	(2.49)	(2.81)	(0.88)	(0.78)	(0.30)	(0.30)	(-0.09)	(0.05)
1998	0.0331*	0.0391*	0.0214	0.0226	0.0170	0.0170	0.0113	0.0059
	(2.43)	(2.63)	(1.22)	(1.30)	(0.69)	(0.69)	(0.44)	(0.23)
1999	0.0284*	0.0305*	0.0132	0.0159	0.0044	0.0044	-0.0071	-0.0039
	(2.29)	(2.08)	(0.86)	(1.05)	(0.20)	(0.20)	(-0.30)	(-0.16)
2000	0.0403**	0.0423*	0.0229	0.0265	0.0031	0.00315	0.0071	0.0090
	(2.72)	(2.62)	(1.18)	(1.37)	(0.14)	(0.14)	(0.29)	(0.36)
2001	0.0245	0.0283*	0.0032	0.0090	-0.005	-0.0059	0.0087	0.0044
	(1.74)	(2.21)	(0.24)	(0.68)	(-0.32)	(-0.32)	(0.39)	(0.20)
2002	0.0151	0.0172	0.0260	0.0219	0.0007	0.0007	0.0225	0.0022
	(0.89)	(1.03)	(1.31)	(1.17)	(0.04)	(0.04)	(0.86)	(0.087)
2003	0.0358	0.0352*	0.0140	0.0103	-0.0010	-0.0010	0.0501	0.0234
	(1.97)	(2.02)	(0.78)	(0.59)	(-0.05)	(-0.05)	(1.81)	(0.88)
2004	0.0305	0.0305	0.0117	0.0092	0.0138	0.0138	0.105*	0.099*
	(1.80)	(1.83)	(0.76)	(0.70)	(0.71)	(0.71)	(2.47)	(2.52)
2005	0.0554**	0.0544**	0.0005	0.0005	-0.0099	-0.0099	0.0128	0.0068
	(2.90)	(2.92)	(0.04)	(0.04)	(-0.58)	(-0.58)	(0.71)	(0.38)
2006	0.040***	0.038***	0.0051	0.0034	-0.0157	-0.0157	0.0527	0.0475
	(4.63)	(3.86)	(0.25)	(0.18)	(-0.84)	(-0.84)	(1.62)	(1.55)
2007	0.0416*	0.0379*	-0.00	-0.0087	-0.0091	-0.0091	-0.0025	0.0012
	(2.32)	(2.05)	(-0.42)	(-0.46)	(-0.49)	(-0.49)	(-0.12)	(0.06)
2008	0.0247	0.0215	0.0007	-0.0015	-0.0008	-0.0008	0.061*	0.06**
	(1.66)	(1.43)	(-0.04)	(-0.08)	(-0.05)	(-0.05)	(2.26)	(2.67)
2009	0.0491	0.0500*	0.0101	0.0047	-0.0115	-0.0115	0.0436	0.0292
	(1.86)	(2.09)	(0.46)	(0.25)	(-0.55)	(-0.55)	(1.66)	(1.17)
2010	0.0369*	0.0338	-0.014	-0.0168	-0.0218	-0.0218	0.0279	0.0177
	(2.26)	(1.78)	(-0.73)	(-0.89)	(-1.27)	(-1.27)	(1.27)	(0.89)
2011	0.0357	0.0326	-0.007	-0.0093	-0.0138	-0.0138	0.057*	0.0409
	(1.85)	(1.66)	(-0.33)	(-0.45)	(-0.63)	(-0.63)	(2.18)	(1.73)
2012	0.0316	0.0338	0.0010	0.0009	-0.0101	-0.0101	0.0486	0.0385
	(1.26)	(1.28)	(0.04)	(0.04)	(-0.52)	(-0.52)	(1.87)	(1.55)
2013	0.0165	0.0177	0.0109	0.00705	-0.0161	-0.0161	0.0309	0.0225
	(0.70)	(0.64)	(0.37)	(0.26)	(-0.86)	(-0.86)	(1.09)	(0.91)

Top number is the coefficient, below in parenthesis is the t-statistic for the dummy variables corresponding to Table 25- Table 28

[1] regressions do not include breeding livestock in measure of investment and total capital assets

[2] regressions include breeding livestock in measure of investment and total capital assets

Table 32: Value of Year Dummies from Pseudo Panel Fixed Effects Regressions by Farm Type for Dairy and Poultry Farms 1996-2013

	Dairy Farms		**Poultry Farms**	
Year	All Farm	By Typology	All Farm	By Typology
1997	-0.0438	-0.0493	0.0289	0.0373
	(-0.82)	(-0.94)	(1.20)	(1.48)
1998	-0.0419	-0.0588	0.0457*	0.0527*
	(-0.70)	(-0.99)	(2.15)	(2.38)
1999	-0.0232	-0.060	-0.0696	0.0467*
	(-1.11)	(-1.16)	(2.51)	(3.40)
2000	-0.0360	-0.0458	0.0519*	0.0590**
	(-0.61)	(-0.83)	(2.69)	(3.21)
2001	-0.0462	-0.0437	0.0568***	0.0477**
	(-0.92)	(-0.81)	(3.82)	(3.47)
2002	-0.0593	-0.0450	0.00754	0.0137
	(-1.00)	(-0.73)	(0.40)	(0.54)
2003	-0.0540	-0.0467	0.0423	0.0406
	(-0.96)	(-0.83)	(1.92)	(1.82)
2004	-0.0135	0.0204	-0.0140	0.00636
	(-0.27)	(-0.26)	(0.86)	(0.24)
2005	-0.0468	-0.0540	0.03(2.75)	0.0322*
	(-0.96)	(-1.08)	71**	(2.27)
2006	-0.0509	-0.0594	0.0162	0.0306
	(-1.00)	(-1.16)	(1.18)	(1.71)
2007	-0.0722	-0.0713	0.0737***	0.0665**
	(-1.33)	(-1.36)	(4.22)	(3.38)
2008	-0.00776	0.00510	0.0349	0.0235
	(-0.13)	(0.08)	(1.25)	(1.04)
2009	-0.0593	-0.0595	0.0115	0.00944
	(-1.03)	(-0.99)	(0.50)	(0.33)
2010	-0.0608	-0.0513	-0.00323	-0.0115
	(-1.06)	(-0.88)	(-0.13)	(-0.48)
2011	-0.0478	-0.0430	0.0301	0.0169
	(-0.82)	(-0.72)	(0.76)	(0.44
2012	-0.0514	-0.0427	-0.00289	-0.0203
	(-0.82)	(-0.65)	(-0.09)	(-0.58)
2013	-0.0531	-0.0484	0.0237	-0.00646
	(-0.89)	(-0.79)	(0.62)	(-0.16)

Top number is the coefficient, below in parenthesis is the t-statistic for the dummy variables corresponding to the regression results in Table *29* and Table *30*

Table 33: Tests for Statistically Significant Time Effects in Fixed Effects Regression with Pseudo Panel Dataset

	Farm Production Type					
	Grain Farms	FNV Farms	Livestock Farms[1]	Livestock Farms[2]	Dairy farms	Poultry Farms
F-Statistic	2.01	1.74	2.24	1.87	2.84	2.66
p-value	0.0321	0.0660	0.0106	0.038	0.0039	0.0067

F-statistic and p-value are from an F-test of the null hypothesis that all of the dummy year variables are not statistically different from zero.
Regressions allowed coefficients to vary by farm typology
[1] regressions do not include breeding livestock in measure of investment and total capital assets
[2] regressions include breeding livestock in measure of investment and total capital assets

7.2 Results for Similar Variables Found in the Literature

Table 34 provides the results of similar coefficients obtained by other studies examining farm capital investment. While many other studies examined farm capital investment, within this table I choose to focus on studies covering investment behavior on farms located in the U.S. within the recent two decades where the authors used panel datasets.

Table 34: Results for Similar Variables Used in Other U.S. Farm Capital Investment Studies

Study	Ariyaratne and Featherstone (2009)	Barry et. al. (2000)	Hadrich and Olson (2013)	Jensen et al. (1993)	Micheels et al. (2004)	Serra et al. (2009)	Weersink and Tauer (1989)
Dataset	Kansas Farm Management Association	Illinois Farm Management Association	North Dakota Farm Ranch Business Association	Kansas Farm Management Association	Illinois Farm Business Management database [A]	Kansas Farm Management Association [B]	New York Dairy Farm Business Summary
Time Period	1998-2007	1987-1994	1993-2011	1973-1988	1995-2002	1997-2001	1974-1983
Estimation method	GMM	GMM	Tobit	OLS DFFITS and Bisquare [C]	OLS	Maximum likelihood and threshold regressions [D]	OLS (LSDV and GLS)
Dependent Variable	farm crop machinery and investment per total capital assets managed	Investment in land and non-land assets divided by capital stock	purchases of machinery divided by GV sales given made a purchase	Investment in land, livestock, machinery, equipment and buildings	Investment [E]	Investment normalized by capital rental rate	Investment in machinery, equipment and livestock changes per unit of capital assets
Coefficient on Farm Income	Cash crop= 0.4334*; Grain= 0.1778*; beef = -0.1887*[F]	0.68*[G]	N/A	0.29* to 0.35*	-0.009* (lagged)	N/A	-0.286* to -0.276*
Coefficient on Output Price Index	N/A	N/A	N/A	N/A	N/A	$8,731-$17,321*[H]	N/A

Table 34 Continued

Study	Ariyaratne and Featherstone (2009)	Barry et. al. (2000)	Hadrich and Olson (2013)	Jensen et al. (1993)	Micheels et al. (2004)	Serra et al. (2009)	Weersink and Tauer (1989)
Coefficient on Depreciation	machinery and equipment depreciation= 4.31*; vehicle depreciation= 4.02*; structure depreciation = -2.831*[I]	N/A	Log of depreciation= 0.01221 (lagged)	0.51* to 0.59* (lagged)	N/A	N/A	N/A
Coefficient on Marginal Tax Rate	N/A	N/A	N/A	-12,753 to -15,699*[J]	N/A	N/A	N/A
Coefficient on Working Capital	N/A	N/A	Log of working capital= -0.0132	N/A	N/A	N/A	N/A
Estimates for other Coefficients of Interest	Non-farm income= -0.08; interest payments= -0.553*		debt to assets= -0.2737*; Livestock farm= -0.1372*[K]; crop farm= -0.0033 [K]	Off-farm income coefficient= 0.08* to 0.15*	Debts to assets= 57.8*; Return on equity= 0.040; Acres= 6.805*	Assets=0.010*[L]; Index of input prices= -16,635[M]*	Change in liabilities= 0.358* to 0.366*; total assets= 2.13* to 2.48*; Size= 0.088[N];

* Indicates the coefficient was statistically significant

[A] included only farms with revenues > $40,000

[B] limited to farms with at least 80% of sales from wheat, corn, grain sorghum and soybeans.

[C] both are variants of OLS that deal with nonnormal errors

[D] separate regressions for farms with: 1) investment <0, 2) investment =0, and 3) investment >0

[E] authors were not clear what was included in investment

[F] these are the average for all farms. Depending on age and asset quartile cash crop income ranges from 0.2078 to 0.6050, grain income ranges from 0.03402 to 0.4811, beef farm income ranges from -0.0955 to 0.3169

Table 34 Continued

[G] these are the average for all farms. Depending on age and credit constraint category the cash flow coefficient ranges from 0.386 to 1.118. The only other variables included in the regression were marginal q and a constant
[H] average capital stock levels are $188,391 resulting in a coefficient value for dollars investment per unit capital stock between 0.04-0.09
[I] these are the average for all farms. Depending on age and asset quartile machinery and equipment depreciation ranges from 2.5957 to 6.7294, motor vehicle and listed property depreciation ranges from 3.2421 to 5.0996; building depreciation ranges from -4.7969 to -1.3445
[J] average level of farm capital is 936,889 so in per capital terms this is equivalent to 0.00136 to 0.0167 dollars per unit capital stock
[K] these are dummy coefficients. The base is a livestock and crop combination farm
[L] lagged value of farms total assets not including investment capital. Included only in regression for investment =0 regime.
[M] Average capital stock levels are $188,391 resulting in a coefficient value of dollars investment per unit capital stock of -0.0883. Included only in regression for investment =0 regime.
[N] measured as dairy farm work units. Was only included in the LSDV regression and not the GLS regression

7.3 Partial Investment Elasticity Estimates

In Figure 7-Figure 12 I provide graphs of the mean and 95% confidence intervals for the partial investment elasticities calculated for the key variables of interest. The 95% confidence interval for the estimated elasticity is indicated by the horizontal line. The estimated elasticity is the number provided to the right of the illustrated confidence interval. The partial investment elasticity is the estimated average $ change in investment given a 1% change in the variable. These are provided separately by farm type and by farm typology, where C= commercial farms, R=resident farms and I= intermediate farms. The stars indicate the level of statistical significance, where *=90%, **=95% and ***=99%.

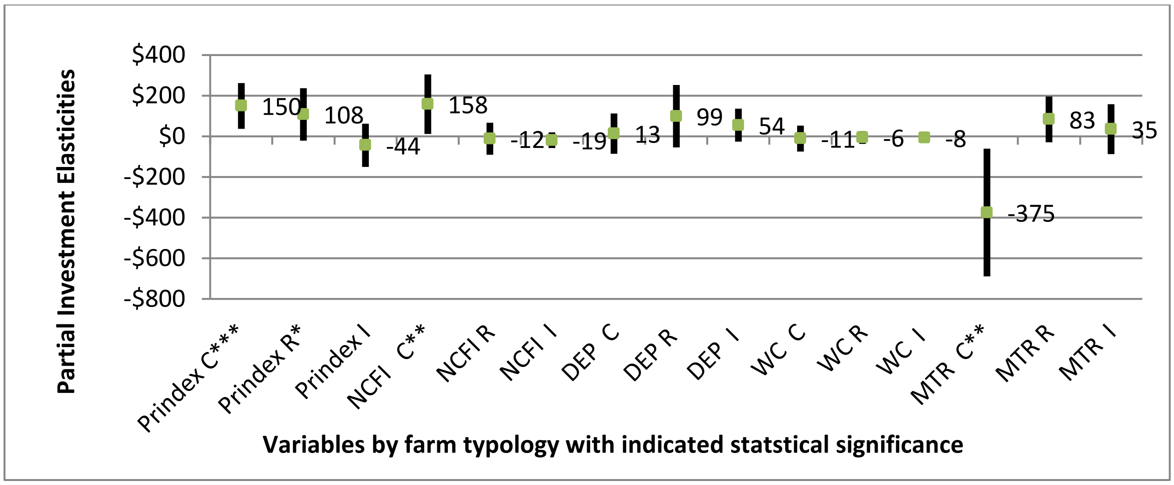

Figure 7: Mean and 95% Confidence Interval for Partial Investment Elasticities for Grain Farms

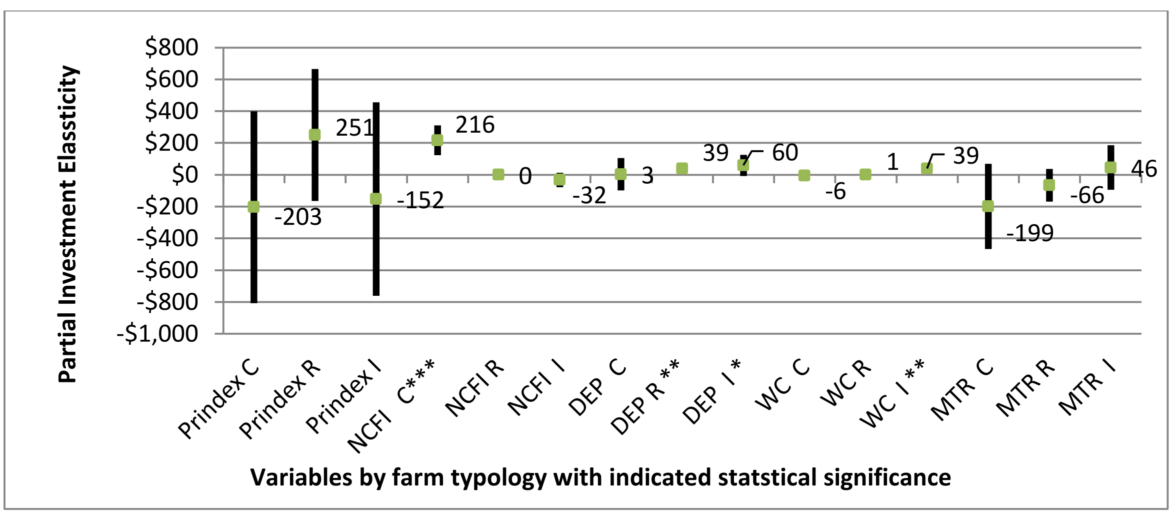

Figure 8: Mean and 95% Confidence Interval for Partial Investment Elasticities for FNV Farms

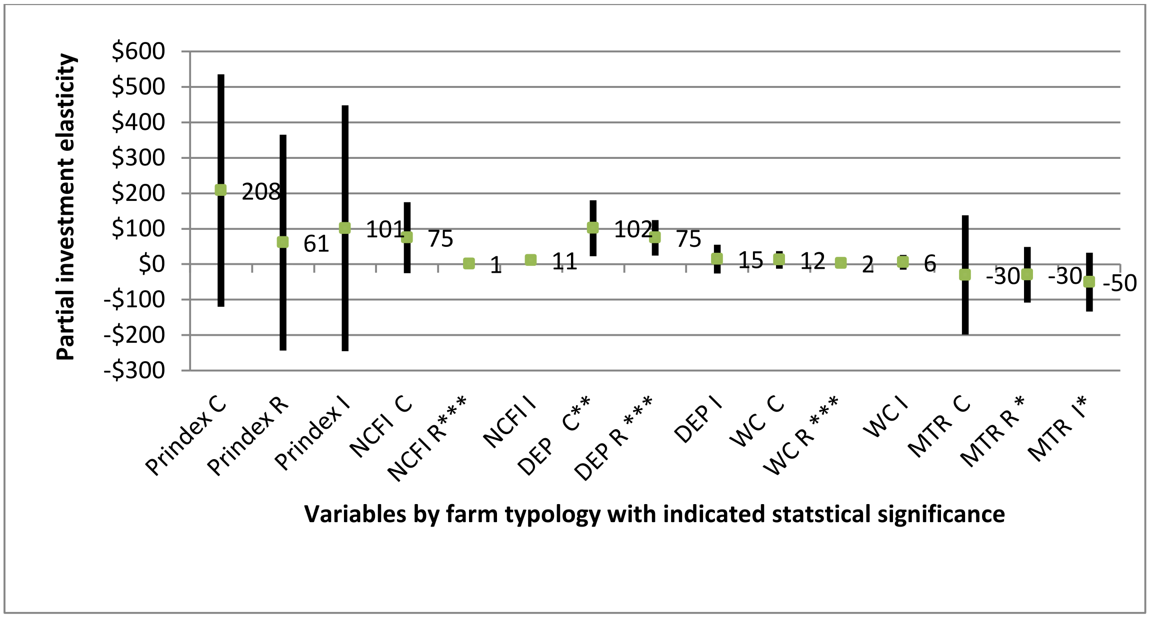

Figure 9: Mean and 95% Confidence Interval for Partial Investment Elasticities for Livestock Farms (not including Breeding Livestock)

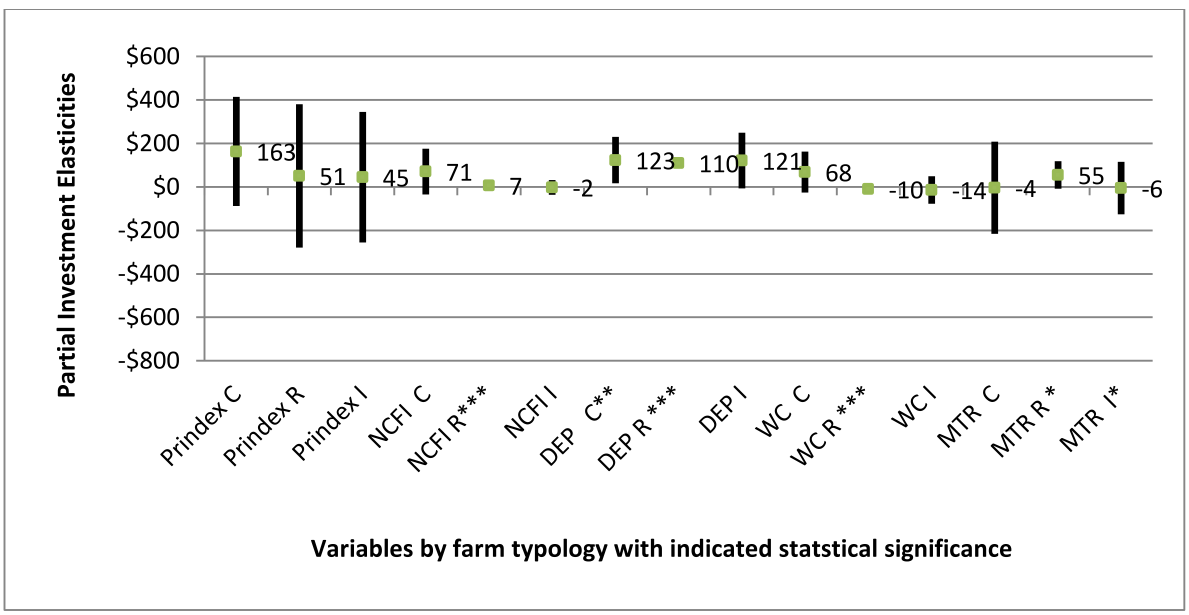

Figure 10: Mean and 95% Confidence Interval for Partial Investment Elasticities for Livestock Farms (including Breeding Livestock)

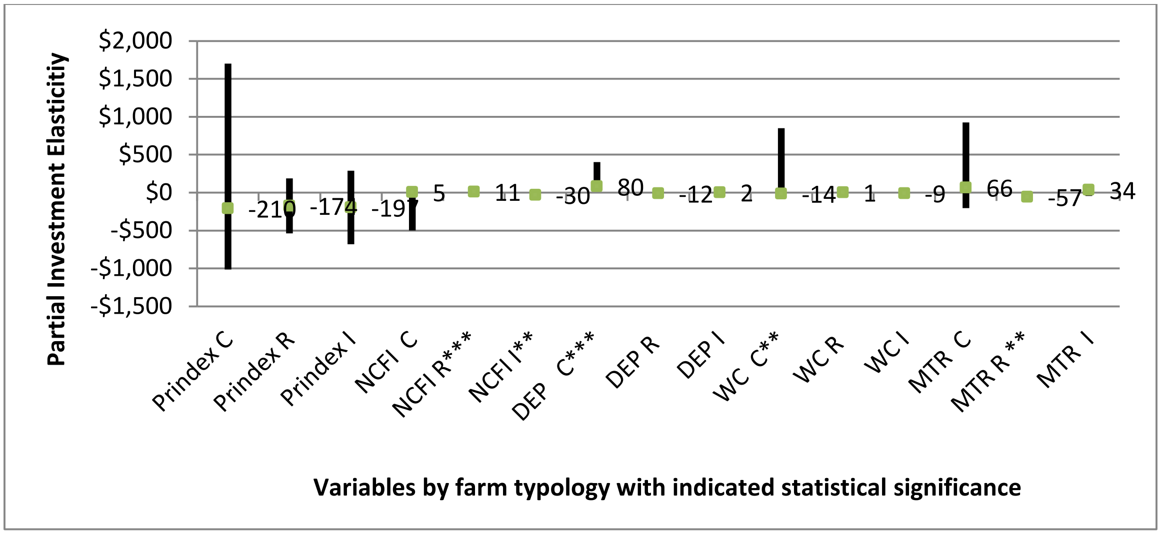

Figure 11: Mean and 95% Confidence Interval for Partial Investment Elasticities for Dairy Farms

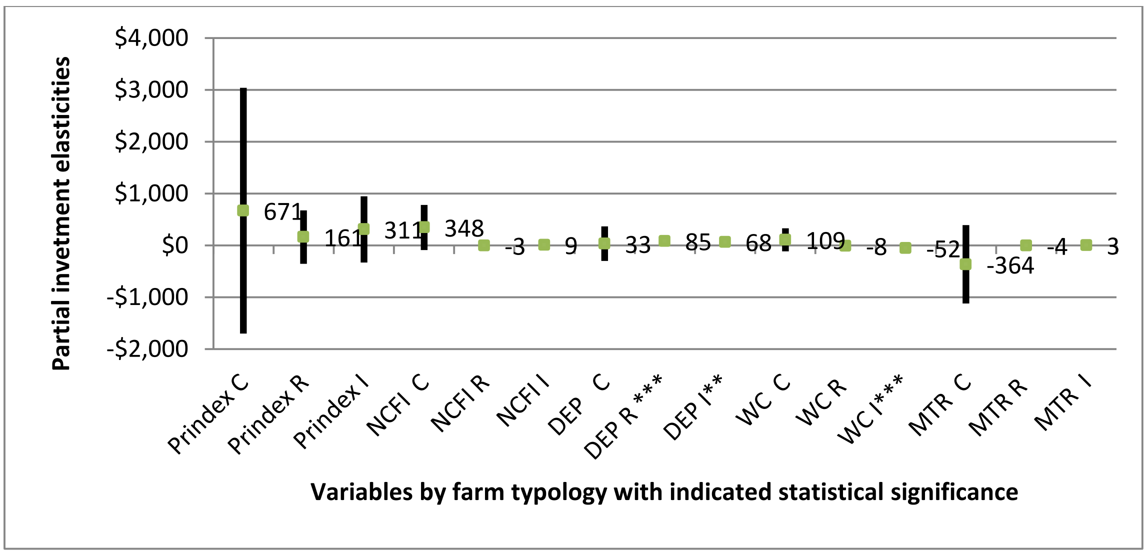

Figure 12: Mean and 95% Confidence Interval for Partial Investment Elasticities for Poultry Farms

7.4 Results for Alternative Measures of Credit and Financial Constraints

Table 35 provides the coefficient values and t-statistics on the variable lagged debts from a regression where this variable replaces the working capital variable in the original model. The regression is performed separately for by farm production type. The first column indicates the value and t-statistic when I constrain this to be equal across all farm typologies. The second through fourth columns indicate the coefficient values where I allow the coefficient values to differ across farm typologies using interaction terms.

Table 36 shows similar results when the working capital variable is replaced with the lagged debt to asset ratio variable. For brevity, the results for the other model variables are not included. These estimates are converted to partial investment elasticities and illustrated in Figure 13-Figure 16. The same procedure was performed for grain farms and poultry farms using lagged debts and debt to asset ratio as well as across all 6 farm production types using lagged net worth levels, but none of the coefficients within these various regressions were statistically significant from zero and hence they are illustrated in the tables above.

Table 35: Selected Results from Pseudo Panel[1] Fixed Effects Regression Results Replacing the Working Capital Variable with Lagged Debts

		By Farm Typology		
Variable Name	Single Coef[2]	Commercial	Resident[3]	Intermediate[3]
		FNV[4] Farms		
$Debts_{t-1}$	-0.00380	-0.00821	0.00663	0.00387
	(-1.60)	(-0.90)	(0.54)	(0.42)
		Livestock[5] Farms (not including breeding livestock)		
$Debts_{t-1}$	-0.00115	-0.000479	0.00236	0.00219
	(0.22)	(-0.07)	(1.07)	(0.99)
		Livestock[5] Farms (including breeding livestock)		
$Debts_{t-1}$	-0.00859*	-0.0126	0.0122	-0.000526
	(-2.21)	(-1.91)	(1.42)	(-0.05)
		Dairy[6] Farms		
$Debts_{t-1}$	-0.0200**	-0.0249**	0.0232	-0.0149
	(-2.91)	(-3.06)	(1.49)	(-1.06)

Top number is the coefficient, below in parenthesis is the t-statistic.
Variables: $Debts_{t-1}$= lagged Farm Total Debt Levels
The dependent variable is investment in machinery, equipment and structures per capital stock.
***=99%, **=95% *=90% Confidence intervals. Robust Standard errors clustered by cohort are used.
[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.
[2] when a single coefficient is estimated for resident, intermediate and commercial farms
[3]these are the difference from commercial farms
[4] This regression includes cohorts where the commodity category is: 1) fruit, nut and vegetable and 2) nursery and horticulture farms.
[5] This regression includes cohorts where the commodity category is: 1) beef, hog and sheep, 2) dairy, and 3) poultry.
[6]This regression includes cohorts where the commodity type category is dairy

Table 36: Selected Results from Pseudo Panel[1] Fixed Effects Regression Results Replacing Working Capital with Lagged Debt to Asset Ratio

		By Farm Typology		
Variable Name	Single Coef[2]	Commercial	Resident[3]	Intermediate[3]
		FNV[4] Farms		
$DTAR_{t-1}$	-0.0000883	-0.000174	0.000161	-0.000430
	(-1.32)	(-0.94)	(0.73)	(-1.46)
		Livestock[5] Farms (not including breeding livestock)		
$DTAR_{t-1}$	0.00000241	0.00000758***	-00000657	-0.0000212**
	(0.57)	(4.16)	(0.29)	(-3.28)
		Livestock[6] Farms (including breeding livestock)		
$DTAR_{t-1}$	0.0000153*	0.0000249***	-0.000109	-0.0000409***
	(2.13)	(7.18)	(-0.37)	(-4.97)
		Dariy[7] Farms		
$DTAR_{t-1}$	0.0000337**	0.0000453*	-0.000394	-0.000216
	(2.89)	(2.60)	(-0.67)	(-0.19)

Top number is the coefficient, below in parenthesis is the t-statistic.
Variables: $DTAR_{t-1}$= lagged Debt to Asset Ratio
The dependent variable is investment in machinery, equipment and structures per capital stock.
***=99%, **=95% *=90% Confidence intervals. Robust Standard errors clustered by cohort are used.
[1]Psuedo panel dataset 1 constructed from ARMS data was used. This panel groups farms based on 5 regions, 9 commodity types, and 3 farm typologies.
[2] when a single coefficient is estimated for resident, intermediate and commercial farms
[3]these are the difference from commercial farms
[4] This regression includes cohorts where the commodity category is: 1) fruit, nut and vegetable and 2) nursery and horticulture farms.
[5] This regression includes cohorts where the commodity category is: 1) beef, hog and sheep, 2) dairy, and 3) poultry.
[6]This regression includes cohorts where the commodity type category is dairy

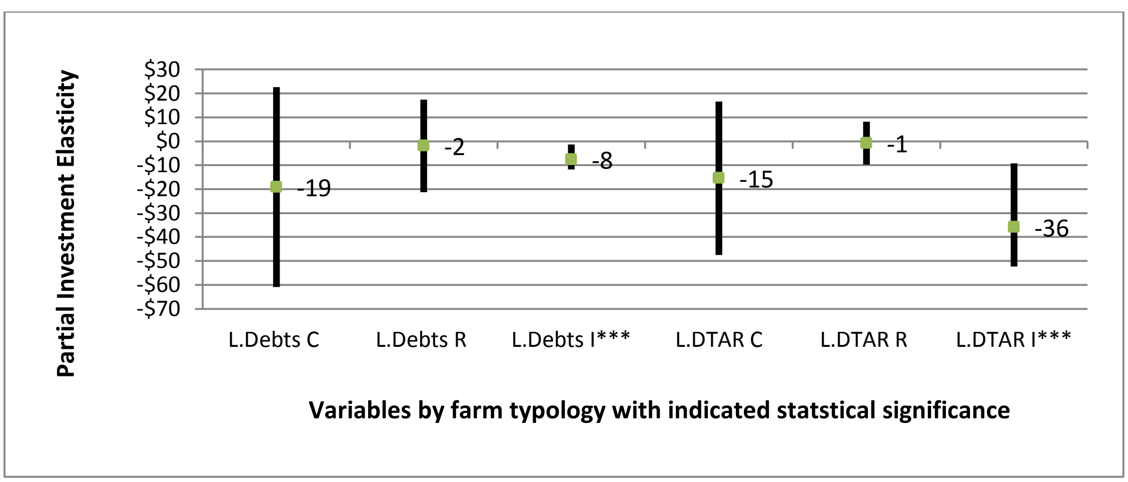

Figure 13: Mean and 95% Confidence Intervals for Partial Investment Elasticities for FNV Farms

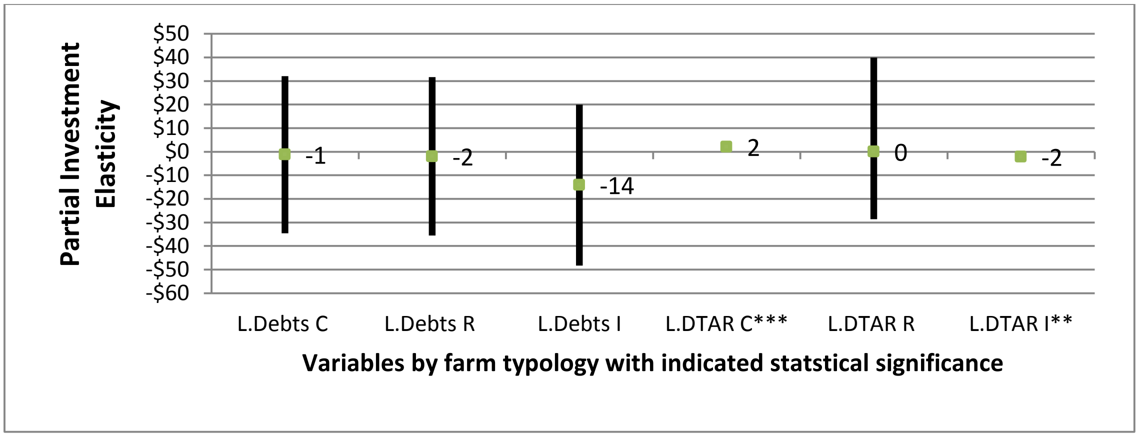

Figure 14: Mean and 95% Confidence Intervals for Partial Investment Elasticities for Livestock Farms (not including Breeding Livestock)

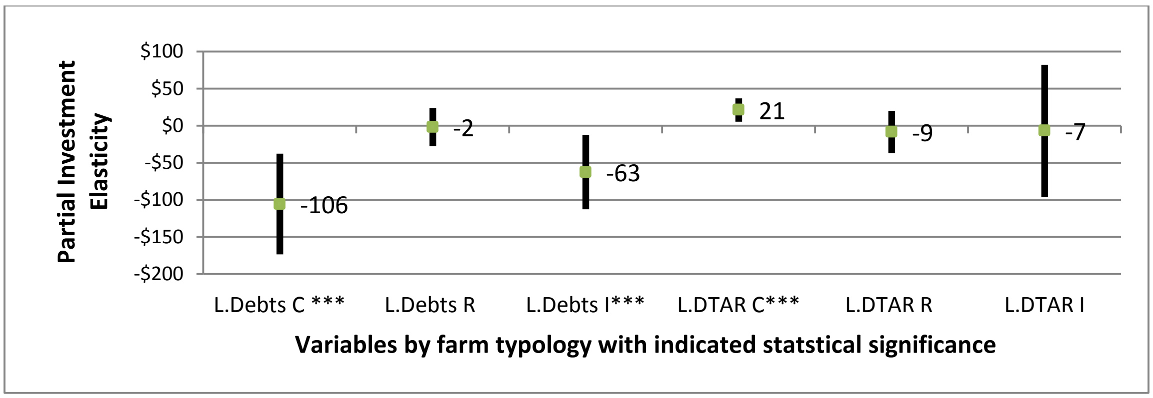

Figure 15: Mean and 95% Confidence Intervals for Partial Investment Elasticities for Livestock Farms (including Breeding Livestock)

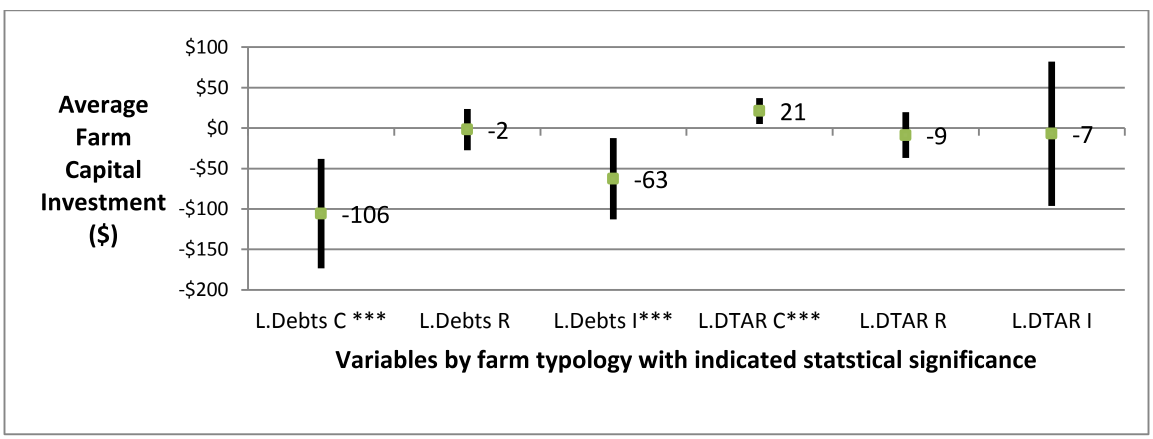

Figure 16: Mean and 95% Confidence Intervals for Partial Investment Elasticities for Dairy Farms

7.5 Comparison Across Alternative Pseudo Panels and Cross Section

Below I provide estimates of the coefficient values and t-statistics for selected variables using the alternative panels constructed. Table 37 – Table 41 provides the results for pseudo panel 2 separately by farm production type, Table 42 for pseudo panel 3, and Table 43 for pseudo panel 3 separately for farms in region 3.

Table 37: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 2[1] for Grain[2] Farms

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[3]
PrIndex	0.0144	-0.0458*	-0.0306
	(0.71)	(-2.03)	(-1.42)
NCFI	0.0383*	-0.0127	-0.0473*
	(2.53)	(-0.50)	(-2.53)
$NCFI^2$	0.00137	-0.00306	-0.00133
	(1.57)	(-1.97)	(-1.53)
DEP	0.224	0.431*	0.359
	(1.30)	(2.08)	(1.33)
MTR	0.00191	0.101	0.0284
	(0.02)	(1.02)	(0.32)
WC	0.00468	0.0199	-0.00682
	(0.46)	(1.01)	(-0.64)
Observations	2,509		
R^2	0.159		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used. ***=99%, **=95% *=90% Confidence intervals.

The dependent variable is investment in machinery, equipment and structures per capital stock.

The above variables varied according to farm typology. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 2 constructed from ARMS data was used. This panel groups farms based on 10 farm production regions, 19 commodity types, and 3 farm typologies.

[2]This regression includes cohorts which fall into the commodity type: 1) cash grains and 2) tobacco and cotton farms. This does not include other crop farms.

[3] these are the difference from commercial farms

Table 38: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 2[1] for FNV[2] Farms

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[3]
PrIndex	-0.308*	0.235*	0.219
	(-2.16)	(2.01)	(1.72)
NCFI	0.0778	-0.053	-0.182*
	(1.05)	(-0.66)	(-2.10)
$NCFI^2$	0.0203	-0.011	0.121
	(1.43)	(-0.48)	(1.48)
DEP	-0.115	0.943**	0.392
	(-0.70)	(3.15)	(1.51)
MTR	-0.374	0.479*	0.528**
	(-1.94)	(2.58)	(2.87)
WC	0.0889	-0.086	-0.0685
	(1.85)	(-1.82)	(-1.35)
Observations	991		
R^2	0.495		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

The above variables varied according to farm typology. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 2 constructed from ARMS data was used. This panel groups farms based on 10 farm production regions, 19 commodity types, and 3 farm typologies.

[2]This regression includes cohorts which fall into the commodity type: 1) fruit, nut and vegetable and 2) nursery and horticulture farms.

[3] these are the difference from commercial farms

Table 39: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 2[1] for Livestock[2] Farms

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[3]
PrIndex	0.107*	0.016	0.00552
	(2.26)	(0.29)	(0.16)
NCFI	0.0338	-0.165*	-0.0195
	(1.59)	(-2.35)	(-0.75)
$NCFI^2$	-0.00265	0.0679*	0.00402
	(-1.65)	(2.11)	(1.75)
DEP	0.0624	0.285*	0.0336
	(1.02)	(2.18)	(0.35)
MTR	-0.0716	0.0767	0.0201
	(-1.04)	(0.82)	(0.22)
WC	-0.005	-0.002	-0.014
	(-0.52)	(-0.16)	(-0.85)
Observations	890		
R^2	0.188		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

The above variables varied according to farm typology. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 2 constructed from ARMS data was used. This panel groups farms based on 10 farm production regions, 19 commodity types, and 3 farm typologies.

[2]This regression includes cohorts which fall into the commodity type: 1) beef, hog and sheep, 2) dairy, and 3) poultry.

[3] these are the difference from commercial farms

Table 40: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 2[1] for Dairy [2] Farms

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[3]
PrIndex	-0.142	0.0231	0.0853
	(-0.72)	(0.15)	(0.57)
NCFI	-0.0318	-0.471*	0.0503
	(-0.48)	(-2.42)	(0.35)
$NCFI^2$	0.00516	-0.455*	-0.278
	(0.67)	(-2.60)	(-0.66)
DEP	0.0261	1.117	0.261
	(0.13)	(1.48)	(0.61)
MTR	0.0727	0.185	-0.201
	(0.21)	(0.47)	(-0.48)
WC	0.0956	-0.0966	0.125
	(1.19)	(-0.99)	(0.49)
Observations	217		
R^2	0.304		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

The above variables varied according to farm typology. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 2 constructed from ARMS data was used. This panel groups farms based on 10 farm production regions, 19 commodity types, and 3 farm typologies.

[2]This regression includes cohorts which fall into the commodity type dairy.

[3] these are the difference from commercial farms

Table 41: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 2[1] for Poultry [2] Farms

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[3]
PrIndex	0.0649	0.0071	-0.00074
	(0.75)	(0.13)	(-0.02)
NCFI	0.0672	-0.291*	-0.159
	(1.01)	(-2.12)	(-1.10)
$NCFI^2$	-0.0336	0.509*	1.263
	(-0.34)	(2.08)	(1.29)
DEP	0.253*	0.581**	-0.0693
	(2.18)	(3.23)	(-0.45)
MTR	-0.05	0.0598	0.104
	(-0.54)	(0.48)	(1.04)
WC	0.00119	-0.0273	-0.0569
	(0.04)	(-0.74)	(-1.20)
Observations	441		
R^2	0.557		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

The above variables varied according to farm typology. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 2 constructed from ARMS data was used. This panel groups farms based on 10 farm production regions, 19 commodity types, and 3 farm typologies.

[2]This regression includes cohorts which fall into the commodity type poultry.

[3] these are the difference from commercial farms

Table 42: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 3[1] and All Regions

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[2]	Intermediate[3]
PrIndex	0.0484	-0.0808**	-0.0438
	-1.35	(-3.05)	(-0.95)
NCFI	0.0417	-0.133	0.168
	-0.32	(-0.75)	-1.15
$NCFI^2$	0.0592	0.104	-0.551**
	-0.41	-0.38	(-2.88)
DEP	0.319	-0.432	0.533
	-1.03	(-0.89)	-1.19
MTR	-0.199*	0.0623	0.276*
	(-2.34)	-0.86	-2.28
WC	0.021	0.00952	-0.0241
	-0.61	-0.22	(-0.42)
Observations	648		
R^2	0.316		

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.

The dependent variable is investment in machinery, equipment and structures per capital stock.

***=99%, **=95% *=90% Confidence intervals.

The above variables varied according to the percentage of both resident and intermediate farms in each cohort. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.

[1]Psuedo panel dataset 3 constructed from ARMS data was used. This panel groups farms based on 9 ERS production regions and 4 acre quartiles.

[2] these are the coefficients and t-statistics on the variable times the percent of resident farms in the cohort

[3] these are the coefficients and t-statistics on the variable times the percent of intermediate farms in the cohort

Table 43: Coefficient Values and T-statistics for Selected Variables Using Pseudo Panel Dataset 3[1] in Northern Great Plains Region[2]

Variable Name	Coefficient Value By Farm Typology		
	Commercial	Resident[3]	Intermediate[4]
PrIndex	0.412	-0.493	-0.35
	(1.19)	(-2.33)	(-1.12)
NCFI	3.578	-3.692*	-3.604
	(2.97)	(-3.29)	(-2.56)
$NCFI^2$	-4.37	4.427	3.21
	(-2.81)	(1.96)	(1.74)
DEP	-2.561	3.404	4.397*
	(-2.31)	(2.70)	(4.74)
MTR	-2.784	2.866*	3.531*
	(-2.94)	(3.6)	(3.4)
WC	0.0122	0.101	-0.0633
	(0.04)	(0.42)	(-0.16)
Observations	72		
R^2	0.69		

Table 43: Continued

Top number is the coefficient, below in parenthesis is the t-statistic. Robust Standard errors clustered by cohort are used.
The dependent variable is investment in machinery, equipment and structures per capital stock.
***=99%, **=95% *=90% Confidence intervals.
The above variables varied according to the percentage of both resident and intermediate farms in each cohort. A single coefficient was included and not listed above for acres, entropy, OFFI, and year dummies. The resulting coefficients were statistically insignificant for these coefficients.
[1]Psuedo panel dataset 3 constructed from ARMS data was used. This panel groups farms based on 9 ERS production regions and 4 acre quartiles.
[2] Included in the region are farms in which the cohort ERS production region is the Northern Great Plains
[3] these are the coefficients and t-statistics on the variable times the percent of resident farms in the cohort
[4] these are the coefficients and t-statistics on the variable times the percent of intermediate farms in the cohort

CHAPTER 8: DISCUSSION OF REGRESSION RESULTS

Within this section I discuss the overall goodness of fit of my regressions, evaluate my hypothesis, and discuss some of the findings for other variables as well as alternative specifications for the model.

8.1 Overall Goodness of Fit

The R^2 values I obtain range between 0.264-0.266 for grain and FNV farms, 0.17 for livestock without including breeding livestock 0.44 when I include breeding livestock, 0.19 for dairy farms and 0.57 for poultry farms. The fit of the regressions improve when I allow the chosen coefficients to vary across typology. This is indicative of the lower RMSE values when I allow for resident and intermediate variable interaction terms on key model variables compared to estimating the regressions with only a single coefficient across all farm typologies for these same variables. Within the regressions, many of the coefficient values are insignificant. One reason could be the lower level of variation between cohort observations compared to that present within the sample data. Another reason could be that in estimating the fixed effects model and including dummy time coefficients, a portion of the variation that would otherwise be explained by the model variables is explained by the fixed effects terms and/or year time dummies. Including these will potentially lead to smaller, though more accurate, variable coefficient estimates compared to studies for which fixed effects and independent year effects exist but are not estimated. In chapter 9, I will demonstrate that regardless of the low R^2 values and small number of statistically significant coefficient estimates, the grain and livestock (without breeding livestock) regressions adequately explain changes in investment over the sample time period given changes in the model variables.

8.2 Results for Hypothesis 1: Output Prices

An increase in output prices results in a statistically significant increase in investment for commercial grain farms. On average, a one percent increase in output prices leads to a $150 increase in investment for commercial grain farms and a $108 increase for resident grain farms. My results for grain farms are similar to Serra et al. (2009). They also estimate that an increase in the value of an index of agricultural output prices results in a positive and statistically significant increase in farm capital investment using data from the Kansas Farm Management Association database over the period of 1997-2001. Unlike Serra et al. (2009) the coefficients are not statistically significant for livestock farms.

One reason why I obtain insignificant coefficients for livestock farms and on commercial FNV farms may be the greater level of heterogeneity within the FNV and livestock farms in my sample compared to that of Serra et al. Serra et al., used farms located only in Kansas and belonging to the Kansas Farm Management Association. In contrast, the ARMS sample encompasses farms located across 48 U.S. states. Within the greater U.S. I would expect there to be a wide variety in the type of FNV crops and livestock products produced across the U.S., leading to a greater variation in average farm investment responses given changes in output prices. The wide range of responses across farms given changes in output prices is illustrated when one examines the large confidence intervals obtained for the FNV and livestock output price partial investment elasticities. In contrast, within grain farms the confidence intervals on output price partial investment elasticities are smaller. One could draw the conclusion that within the ARMS sample there is a greater level of homogeneity in across grain farms in response to changes in output prices compared to that found across different FNV and livestock production types. This results in a greater ease in quantifying the impacts for changes in output prices across grain farms compared to FNV and livestock farms.

I can accept hypothesis one for commercial grain farms. Investment rates for commercial grain farms respond to a greater degree given a change in output prices compared to commercial and resident grain farms. This is indicated by the negative and statistically significant interaction term on output prices for intermediate grain farms. In fact, the partial investment elasticity on output prices is not statistically different from zero for intermediate grain farms. I cannot conclude that an increase in output prices has a statistically significant impact on intermediate grain farm investment. Within livestock farms, I am inclined to conclude that that the same relationship exists and commercial livestock farm investment is more responsive to changes in output prices compared to intermediate livestock farm investment, given the negative estimated interaction terms and lower partial investment elasticity estimates for resident and intermediate livestock farms compared to commercial livestock farms. Unfortunately, due to lack of statistical significance, I must reject hypothesis one for commercial livestock farms.

I reject hypothesis one with regards to output prices for FNV farms. There is a statistically significant and positive coefficient on the interaction term for resident FNV farms, indicating that the rate of investment increases more given an increase in output prices for resident FNV farms compared to commercial FNV farms. The large resident FNV farm output price partial investment elasticity estimate indicates that resident FNV farms are extremely responsive the changes in output prices. On average, a one-percent increase in output prices will generate a $251 increase in farm capital investment for resident FNV farms. I cannot make any conclusions regarding intermediate vs. commercial farm investment in responses to changes in output prices given the lack of statistical significance of my estimated commercial farm coefficient and the intermediate farm interaction term.

8.3 Results for Hypothesis 1: Returns on Investment

Past studies for crop or mixed crop and livestock farms overwhelmingly find a positive and statistically significant relationship between investment and increases in farm income and the returns to investment. These include: Jensen et al. (1993) for investment in land, livestock, machinery, equipment and buildings by farms in the Kansas farm management dataset over the period of 1973-1988, Ariyarante and Featherstone (2009) using the same dataset over the period of 1998-2007 for the rate of investment in farm machinery and equipment, and Barry et al. (2000) for investment in land and non-land assets using the Illinois Farm Management Association database for years 1987-1994. Similar to these studies, my estimated coefficients are statistically significant and positive for commercial grain and FNV farms. On average a 1% increase in the returns to investment income results in a $158 increase in commercial grain farm investment and a $216 increase in commercial FNV investment.

Looking only at livestock farms, Ariayante and Featherstone (2009) obtain negative and statistically significant coefficient estimates on beef farm income. Similarly, Weersink and Tauer (1989) estimate that an increase in income for New York Dairy Farms leads to statistically significant decrease in machinery, equipment, and livestock investment. In contrast to these studies, the coefficient estimates and partial elasticity estimates on the returns to investment for commercial livestock farms are positive but not statistically different from zero. I cannot reject that changes in the returns to investment have no impact on commercial livestock investment.

There are multiple reasons why my results for livestock farms may differ from those of Ariayante and Featherstone (2009) and Weersink and Tauer (1989). One reason could be the greater level of heterogeneity between livestock producers within my sample. Since my dataset covers the whole US rather than a single state, it includes a greater variety of animal production systems. Believing that that the response to changes in net farm income differs according to animal production type, it is logical that having a greater variety of animal production types in the sample may lead to a greater range of estimates and difficulty in finding statistical significance.

To address this issue, I estimate the regression for dairy and poultry separately. I obtain similar results for poultry farms as I do for livestock farms as a whole. For dairy farms my results now match those of other studies. There is a statistically significant and negative coefficient on the returns to investment and a smaller but positive statistically significant coefficient on investment returns squared. It appears that the rate of investment is negatively correlated with increases in the returns to investment. This may be related to the livestock production cycle, where changes in prices and income levels encourage producers to either build or reduce herd sizes.

I can accept hypothesis one for grain and FNV farms. The interaction terms for intermediate grain farms as well as intermediate resident and intermediate FNV farms are negative and statistically significant. An increase in the returns to investment encourages a larger increase in the rate of investment on commercial grain farms compared to intermediate grain farms and on commercial FNV farms compared to either resident or intermediate FNV farms. I cannot conclude that there is any difference in the rate of investment on resident farms compared to commercial grain farms given the lack of significance of the interaction term on resident grain farm returns.

Interestingly, for resident and intermediate grain and FVN farms the coefficient on the squared term is generally positive while it is negative for commercial grain and FNV farms. In general, the opposite is true for resident and intermediate farms. This results in the following relationship: for intermediate and resident farms: increases in returns have a greater impact on investment given higher initial farm income levels while they have a greater impact on commercial farms at lower initial farm income levels. As a result, the response to a change in the returns to investment will be the most similar for farms in the middle of the income distribution range. In general, very low income intermediate and resident farms will be the least responsive to a change in the returns to investment.

Hypothesis one is more difficult to interpret for livestock farms given the lack of statistical significance on commercial farm coefficients and the squared income term I use. I obtain a statistically significant and negative interaction term on resident farms when breeding livestock is included but a positive interaction term for intermediate farms when breeding livestock is not included. When I look at dairy separately, I obtain no difference between resident and commercial responses to a change in the returns to investment but that intermediate dairy farms increase the rate of more given an increase in returns. For poultry farms both the commercial farm and the interaction term coefficients are statistically significant, indicating that an increase in investment returns has no impact across any of the farm typologies. Looking at the estimated partial investment elasticities, it appears that commercial livestock, dairy, and poultry farm investment increases to a greater degree given a change in returns, but this could be mainly due to the large levels of capital stock on commercial farms vs. higher rates of investment.

8.4. Results for Hypothesis 2: Marginal Tax Rates

A change in marginal tax rates has a statistically significant impact only commercial farms within the grain farms production category. There is a negative relationship between commercial grain farm investment and marginal tax rates. A one percentage increase in the marginal tax rate leads to a $375 decrease in commercial grain farm capital investment. My results for commercial grain farms are similar to that of Jensen et al. (1993). They estimate that an increase in the calculated farm marginal tax rate results in a statistically significant decrease in investment.

Unlike Jensen et al. (1993), I obtain statistically insignificant coefficients on marginal tax rates for commercial farms in all other production types. This difference in statistical significance for FNV and livestock farms may be linked to differences in estimated levels and variation of farm marginal tax rates. The mean and standard deviation of marginal tax rates for farms in Jensen et al.'s Kansas Farm Management Dataset sample is larger than those estimated for cohorts in the ARMS dataset. Jensen et al. (1993) estimate that during the 1973-1988 time period the average marginal tax rate for farms in the Kansas Farm Management Dataset was 0.30 with a standard deviation of 0.223. The average marginal tax rate for cohorts within the sample is 0.16 with a standard deviation of 0.07. These differences could be due to differences in federal tax rates during the different sample time period, differences in farm crop and livestock production choices and related farm income levels, or the use of pseudo panels vs. true panel data. Regardless, at lower tax rates an increase in the marginal tax rate could have less of an impact on investment then at higher marginal tax rates. At these lower rates a change in the marginal tax rate could have a smaller impact on investment. In addition, Jensen et al. (1993) uses a Bisquare OLS estimation methodology while this study uses a fixed effects methodology. His methodology accounts for outliers in the data while mine focuses on fixed effects related to differences in farm size, production region, and production type. These differences in estimation methodologies may lead to differences in coefficient estimates.

Hypothesis two is supported for grain farms, though different than what I expected. An increase in investment leads to a slightly larger increase in investment for resident farms compared to intermediate farms. Compared to commercial farms, the impact of an increase in marginal tax rates on resident farm investment is not "larger or stronger" as much as it is "different". On average, an increase in the marginal tax rate leads to a $375 decrease in commercial grain farm investment and a $83 increase in resident farm investment and a $35 increase in intermediate grain farm investment. Higher levels of investment reduce total taxable income. Taking advantage of this tax benefit should be more attractive as off-farm income levels increase. This explains the larger impact of marginal tax rates on resident grain farms compared to intermediate grain farms. One would expect the same relationship for commercial grain farms, as the summary statistics show that they also earn high levels of off-farm income. One explanation for this negative relationship could be when the marginal tax rate increases, either due to increases in the tax bracket percentages or because higher farm incomes push the farm into a higher tax bracket, the impact of a reduction in total income available for investment is greater than the benefits of reducing off-farm taxable income through investment. The overall result is a decrease in investment given an increase in marginal tax rates. It appears that the same relationship holds for FNV farms, livestock farms (including breeding livestock), and poultry farms. Unfortunately, given the lack of statistical significance on these coefficients for the other farm production types, I cannot reject that changes in marginal tax rates have no impact on resident farm investment within these categories.

8.5 Results for Hypothesis 2: Tax Depreciation Expenses

Increases in the depreciation tax rate[17] are associated with greater investment on livestock farms. For every one percent increase in the depreciation tax rate investment on commercial livestock farms increases by \$102 and \$123, depending if breeding livestock is included or not. This impact holds if livestock farms are split into more homogeneous categories. A one percent increase in the depreciation tax rate results in a \$198 increase in commercial dairy investment and \$33 in commercial poultry investment. The estimated coefficients are

---

[17] The level of tax depreciation expenses is also related to the level of investment as seen in Table 23. Unfortunately, the link between larger farms having on average larger levels of revenues, expenditures, income, and asset levels makes using depreciation expenses without adjusting for differences in farm size problematic. By normalizing by capital expenses I minimize multicollinearity between model variables. Another way to address this would be to instead use a measure of allowable tax depreciation rates. This methodology along with pseudo panels constructed from ARMS data was used in a soon to be published article by Williamson and Stutzman in the *Agricultural Finance Review*. This methodology minimizes multicollinearity and deals with potential endogeneity due to greater depreciation expense levels caused by larger capital stock levels as a result of greater investment that period. This method does not take into account the actual level of depreciation taxes taken that period. Given generous tax depreciation expensing limits and bonus depreciation expense rates in the later part of our sample period, many farms expensed the majority of capital purchases in the given purchase period (Williamson and Stutzman). As a results, allowable and actual tax depreciation rates may differ substantially in the later sample time period.

statistically insignificant for commercial grain and FNV farms. A change in depreciation tax expenses have no statistically significant impact on commercial grain and FNV investment.

In comparison, Ariyarante and Featherstone (2009) obtain statistically significant estimates for machinery and equipment depreciation, vehicle depreciation and structure depreciation across the whole sample and within specific constructed farm quartiles. They estimate that an increase in lagged machinery and vehicle tax depreciation expenses results in an increase in investment, while an increase in lagged structure depreciation expenses results in a decrease in investment. Smaller but also positive and statistically significant increases in investment per dollar of lagged tax depreciation expenses were obtained by Jensen et al. (1993). In contrast, Hadrich and Olson (2013) estimate a statistically insignificant coefficient on the lagged log value of tax depreciation expenses for farms which made an investment in the given period.

One reason for the difference in statistical significance and smaller coefficients I and Hadrich and Olson obtain compared to Ariyarante and Featherstone may be the fact that neither I nor they distinguish between different types of capital. If, according to Ariyarante and Featherstone, increases in machinery and equipment depreciation rates lead to increases in investment rates while increases in structure depreciation expenses are associated with decreases in investment, then lumping these categories together will result in either smaller coefficient estimates and/or increase the standard error of the estimated coefficients and lead to statistically insignificant estimates.

The positive and statistically significant interaction term on resident farms supports hypothesis two for livestock farm investment. Resident livestock farms increase their rate of investment to a greater degree given a change in the rate of tax depreciation expenses. A one percent increase in the depreciation tax rate results in a $70 or $110 increase in depreciation for resident livestock farms, depending on if breeding livestock is included or not and a $85 increase in investment for poultry farms. While the rate of investment is greater for resident farms, converting this to dollars of investment results in a smaller partial investment elasticity estimate compared to commercial farms. This is due to the fact that that resident farms, on average, have smaller capital stock levels. Hence, while investment policy may have a larger “impact” on resident farms the actual change in investment expenditures for the sector as a whole from any change in tax rates will be largely determined by the impact of investment by both commercial and resident farms. The statistically insignificant interaction terms on resident and intermediate grain and FNV farms leads me to reject hypothesis two for grain and FNV farms and conclude that there are no statistically different response to marginal tax rates between resident, intermediate, and commercial intermediate grain or FNV farms.

8.6 Results for Hypothesis 3: Working Capital

Changes in working capital levels have little impact on commercial farm investment. Across all of the farm production types, the coefficient on working capital for commercial farms is not statistically different from zero, nor are the majority of the interaction terms on resident or intermediate farms. These results are similar to that of Hadrich and Olson (2013). They also obtain a small and statistically insignificant coefficient on the log of working capital.

I accept hypothesis three for FNV farms. The rate of investment greater on intermediate FNV farms given an increase in working capital levels. Greater levels of internal liquidity on intermediate FNV farms lead to a higher rate of replacement of capital stocks. This supports my hypothesis of credit constrained behavior for intermediate FNV farms. I reject hypothesis three for grain, livestock, dairy and poultry farms. There is no statistically significant differential impact on investment across intermediate grain, livestock, or dairy farms given a change in working capital levels.

While I reject the hypothesis of credit constrained behavior for poultry farms, I do find a linkage between working capital levels and investment on intermediate poultry farms. A decrease in the rate of working capital on intermediate poultry farms is associated with an increase in the rate of investment. There are multiple reasons that could explain this relationship. One potential explanation is that the act of investment leads to a decline in working capital levels on intermediate farms. In this case, the investment funds are obtained from either liquidating short-term assets or taking on additional short-term debt. An alternative explanation is that intermediate poultry farms with lower working capital levels are more likely to have higher investment rates. Further research is needed to determine the impact of poultry contracting relationships on the optimal level of working capital producers choose to hold and the impact on farm investment levels.

8.7 Results for Hypothesis 3: Lagged Debts, Lagged Net Worth, Lagged Debt to Asset Ratio

To verify these results, I examine the impact of other measures of financial constraints on farm capital investment, including lagged net worth, lagged debt, and lagged debt to asset measurements. For grains, FNV and poultry farms I find no statistically significant impacts on the rate of commercial farm capital investment from a change in any of these variables. Lagged debt levels have no statistically significant impact on the rate of commercial farm capital investment, except for dairy farms. Within dairy farms, there is a statistically significant and negative relationship between lagged debts and commercial farm investment. A higher level of debt in the prior period on commercial dairy farms is linked with a reduction in investment in the current period. This appears logical though the nature of the cause is uncertain. Increases in debt over the prior periods may reduce available credit levels this period. The reduction could be imposed externally in the credit markets or by the producer themselves unwilling to take on higher investment. The link between investment and higher prior credit levels could also just reflect the fact that, given the lumpy nature of capital and if it is assumed that some portion of the investment is financed through debt, a large investment yesterday could mean that needed investments will be lower in the current and subsequent periods.

My results for all but dairy farms are different from those obtained by other farm investment studies such as Serra et al., who obtains a positive and statistically significant coefficient on assets, or Weersink and Tauer, whom obtain a positive and statistically significant coefficient on changes in liabilities and assets. One reason may be my sample time period. Farm incomes rose and total debt levels of producers fell during the latter portion of my sample period. Many producers were able to invest out of current earning and hence the level of debts and net worth will have less of an impact in influencing investment levels.

For livestock and dairy farms, I obtain positive and statistically significant coefficients on lagged debt to asset coefficients for commercial farms. A higher level of debts relative to assets last period is associated with greater investment this period. A similar coefficient value was obtained by Micheels et al. (2004) for farms in the Illinois Farm Business Management Association between 1995-2002. In contrast, Hadrich and Olsen (2013) estimate that an increase in the debt to asset ratio leads to a statistically significant decline in farm investment for farms in the North Dakota farm Ranch Business Association between 1993-2011. It could be that within my and Micheels et al.'s studies, the debt to asset ratio coefficient is picking up the relationship between farms which are growing and both tend to have greater than average investment levels and higher debt to asset ratios.

Using the debt to asset ratio, I can only accept hypothesis three for livestock farms. The debt to asset interaction term on intermediate livestock farms is negative and statistically significant. The rate of investment on intermediate farm investment declines as debts increase relative to assets while it increases on commercial livestock farms. A one percent increase in the ratio of debts to assets the prior period results in a $2 or $21 increase in investment in commercial farm investment and a $2 or $7 decline in investment on intermediate farms, depending if breeding livestock is included or not. While the intermediate and commercial farm investment elasticity estimates for dairy and FNV farms exhibit the same relationship, the intermediate farm interaction terms are not statistically significant, hence I cannot conclude that there is any statistically difference across farm typologies in response to a change in the ratio of debts to assets in FNV or dairy farms.

Given these conflicting results, that the impact of credit and financial constraints on investment is different even in similar farm production types depending on the measurement used, further work is needed to be certain regarding the exact relationship between increases in liquidity and financial constraints across farm production types and typologies.

8.8 Results for Other Model Variables: Off-farm Income

In most cases, the estimate partial investment elasticities on off-farm income are small and statistically insignificant. A 1% change in the level of off-farm income results in no statistically significant change in farm investment across any of the enterprise types. Ariyarante and Featherstone (1998) also estimated a statistically insignificant coefficient on off-farm income. In contrast, Jensen et al. (1993) estimated positive and statistically significant coefficients on off-farm income. Both Jensen et al. (1993) and Ariyarante and Featherstone (1998) utilize Kansas Farm Management but examine investment behavior over different time periods. The 1998-2007 time period utilized by Ariyarante and Featherstone (1998) overlaps my sample time period, 1996-2013. Jensen et al. (1993) utilized the earlier time period of 1973-1988. Reasons for these differences may be that in the earlier time period either: off-farm incomes varied more in general and/or in comparison to farm incomes, off farm incomes were much higher in comparison to farm incomes, or a larger portion of farms did not earn off-farm income. A lower level of variation within off-farm income levels overall and compared to farm-income levels during the sample time period, less of a difference between off-farm and farm income levels, or a greater number of farms now earning off-farm incomes would result in smaller and potentially statistically insignificant impacts on investment from a change in the level of farm off-farm income during the 1996-2013 time frame, supporting the lack of statistical significance obtained in my and Ariyarante and Featherstone's estimates.

8.9: Results for Other Model Variables: Farm Acres

The impact of a change in farm acres on investment differ across production types. There are no statistically significant impacts on investment from a change in farm acreage for grain or FNV farms. For livestock farms (excluding breeding livestock), an increase in farm acres results in a statistically significant decrease in investment rates. These results differ from that of Micheels (2004), who estimated a positive and statistically significant relationship between farm capital investment and farm acres using Illinois Farm Business Management data. Unlike Micheels, I normalize by the value of farm capital stock. This removes any spurious correlation between larger investment levels on large farms and acres due to the sole fact that large farms operate a greater number of acres. In addition, Micheels does not differentiate between crop and livestock production when estimating the impact of farm acres on investment. By separating grain, FNV and livestock farms I remove any spurious relationships between acreage and investment that are due to differences between different crop and livestock production systems. In contrast to the findings of Micheels (2004), Weersink and Tauer (1989), find no statistically significant relationship between dairy farm investment and farm size. They utilize work units to measure farm size. This measurement is a more accurate reflection of farm size for livestock farms given that it takes into account physical livestock units produced and is not solely based on physical farm size. When I estimate the regression for dairy farms separately I also obtain a statistically insignificant coefficient on farm acres. Given these conflicting relationships, further work is needed to determine the exact relationship between investment across different livestock production types and physical farm size.

8.10: Results for Other Model Variables: Interest Rate

I would expect an increase in interest rates to both increase the opportunity cost of investing and to deter taking on new loans. Surprisingly, my estimated coefficients and partial investment elasticities for interest rates are statistically insignificant. In contrast, Ariyarante and Featherstone (1998) found a statistically significant and negative coefficient on interest rate expenses. One reason for these differences may be that I use average Federal Reserve District level interest rates rather than interest expenses or the rates paid on individual farm loans. This measurement takes into account time variation in interest rates but does not fully capture the regional variation within different Federal Reserve Districts, farm typologies, or production enterprise types. Nor does it account for variation in actual interest rates paid at the farm level. As a result, using an average of farm interest rates may result in estimates that under-estimate the variation in interest rates faced by farms in a given cohort. Another reason may that during my sample period farm incomes were high allowing many farms to invest using internal funds vs. outside debt. The market interest rate may have had very little impact on investment for these farms.

8.11: Results for Other Pseudo Panels

Comparing my results across other panels supports the initial results found using panel 1. Statistically significant results within the panels match the results found using panel 1. On the other hand, the results obtained within the other panels raises additional questions regarding the ability of pseudo panels to identify important relationships. Fewer of the coefficients are statistically significant when pseudo panel2 is used compared to panel 1. It appears that breaking farms into more categories, and as a result using a fewer number of farms to calculate each cohort means, leads to a smaller ability to identify the impacts of changes in variable values on investment. One thought is that there not enough observations within each category to accurately reflect true population means. In this case, using pseudo panel 2, while resulting in a greater number of categories and better large sample regression properties, does not outweigh the downsides of this panel, which include fewer observations within cohorts and a greater number of missing cohort observations.

When I utilize pseudo panel 2, I obtain negative coefficients on prices and income and positive coefficients on depreciation and tax interaction terms for resident and intermediate farms compared to commercial farms. These further support the results of hypothesis 1 and 2 for grain farms. The impacts of output prices and taxes for resident farms and incomes for intermediate farms are statistically significant. For FNV farms I see similar impacts for incomes and for depreciation and marginal tax rates, again further supporting my results for hypothesis 1 and 2 for FNV farms. I also see a greater impact of an increase in prices on resident FNV farms compared to commercial farms, similar to that found in pseudo panel 1 and contrasting my expected results for hypothesis 1 with regards to output prices in FNV farms. For livestock farms I see very little impact from prices, incomes or marginal tax rates. I find negative interaction terms on output prices and a positive interaction terms on depreciation tax rates for resident and intermediate farms. The coefficients are generally insignificant for commercial farms and the intermediate farms, indicating low overall impacts on investment from changes in these variables. Those for incomes and tax depreciation rates for resident farms are statistically significant, supporting hypothesis 2 and to some degree hypothesis 1. These impacts are similar for dairy and poultry farms as to livestock farms when using pseudo panel 3, further adding credence to these hypotheses. I overall find no statistically significant differences in working capital levels across any of the farm typologies or farm types, further supporting my results for hypothesis 3.

Similar results are obtained in terms of coefficient signs with regards to output prices, income levels, depreciation levels and marginal tax rates when using pseudo panel 3 compared to using pseudo panel 1. One difference is that statistical significance of the coefficients obtained using pseudo panel 3 is lower compared to those obtained when using pseudo panel 1. This supports my thought that by not grouping farms specifically into farm typologies I am less able to clearly identify differences between the responses to key variables among farm typologies. The results obtained in panel 3 support hypothesis 1 for output prices when comparing commercial and resident farms and hypothesis 2 with regards to marginal tax rates when comparing resident and intermediate farms. I reject hypothesis 3, finding no statistically significant impact from a change in working capital levels on farm investment. This proves that my results with respect to working capital are related to my choice of pseudo panel construction. Working capital levels have little impact on the rate of farm capital investment regardless of if cohort categories reflect differences in farm income levels or not. Estimating the regressions separately by region in an attempt to take advantage of production differences resulted in mainly statistically insignificant coefficient estimates. The exception was region 3, where my results are very similar to those obtained for grain farms using pseudo panels 1 and 2.

These comparisons both lend credence to my earlier results, support the need to taking into account differences in farm size and owner occupation when forming cohorts, as well as the difficulty of obtaining statistical significance when estimating using fixed effects models and pseudo panels constructed from highly heterogeneous survey data. Statistically significant impacts for panel 1 in general appear consistent across panel construction while similar but statistically insignificant results in other panels may be statistically significant in panel 1. This is similar to the findings comparing using different models, including random effects and feasible least squares, to a fixed effects model.

CHAPTER 9: APPLYING THE MODEL

In this chapter I use the estimated coefficients and partial investment elasticities to perform two exercises. First, I examine the ability of changes in the model variables between the sample time period of 1996 and 2013 to explain changes in investment levels between these time periods. Next, I estimate the expected change in farm capital investment by 2024 given projected changes in key model variables.

9.1 Differences in Farm Capital Investment in 2013 vs. 1996

Both investment and the other key variables in the model, such as output prices, net farm incomes, depreciation expenses, working capital levels, and interest rates changed dramatically over the sample time period. In this section I draw connections between differences in farm investment levels in 2013 vs. 1996 and differences in output prices, returns, cash flows, tax policy, and interest rates in these two years. I estimate the portion of the difference in investment in 2013 vs. 1996 attributable to changes in each of the model variables both separately and as a whole. These measurements are compared to the portion of investment not explained by changes in the model variables between these two years.

9.1.1 Farm Economy in 2013 Compared to 1996

Table 44-Table 49*: Average Value of Model Variables in 1996 vs. 2013 for Intermediate Livestock Farms* list the average value of each of the model's variables in 2013, in 1996, and the percentage change between the two years by farm typology and enterprise type. For net cash farm income, tax depreciation expenses, working capital and acres I provide estimates below using the observation values, while in the model these are normalized by the level of farm capital stock.

Table 44: Average Value of Model Variables in 1996 and 2013 for Commercial Grain and FNV Farms

	Grain Farm			FNV		
Variable (units)	2013	1996	Change	2013	1996	Change
I($)	74,718	34,641	40,077	62,175	31,603	30,571
K($)	634,771	424,796	209,975	592,504	444,039	148,465
Prindex (index)	1.017	0.646	0.371	1.119	0.726	0.392
NCFI ($)*	229,311	130,242	99,069	334,651	218,324	116,326
DEP ($)*	59,349	33,145	26,204	62,615	45,783	16,832
ACRES*	1,188	1,205	-17	447	337	110
MTR (ratio)	0.206	0.206	-0.001	0.211	0.200	0.010
ENTROPY (index)	0.187	0.205	-0.018	0.051	0.076	-0.025
WC($)*	246,329	113,042	133,287	595,337	120,555	474,782
Intrate (ratio)	0.0449	0.0796	-0.0347	0.0493	0.0791	-0.0298
OFFI (thousand $)	71.804	59.006	12.798	85.840	59.006	26.834

Table 45: Average Value of Model Variables in 1996 and 2013 for Commercial Livestock Farms

	Livestock Farm		
Variable (units)	2013	1996	Change
I ($) [A]	26,121	41,224	-15,103
I ($) [B]	33,248	24,675	8,573
K ($) [A]	581,777	606,827	-25,049
K ($) [B]	448,803	323,991	124,813
Prindex (index)	1.106	0.782	0.324
NCFI ($)*	144,494	129,167	15,326
DEP ($)*	40,603	44,435	-3,831
ACRES*	247	316	-69
MTR (ratio)	0.160	0.164	-0.004
ENTROPY (index)	0.108	0.087	0.021
WC($)*	131,309	105,065	26,245
Intrate (ratio)	0.0458	0.0787	-0.0329
OFFI (thousand $)	69.579	51.535	18.044

[A] does not include breeding livestock
[B] includes breeding livestock

Table 46: Average Value of Model Variables in 1996 and 2013 for Resident Grain and FNV Farms

	Grain Farm			FNV		
I($)	2013	1996	Change	2013	1996	Change
K($)	48,046	17,869	30,178	37,241	14,669	22,572
Prindex (index)	420,658	329,452	91,206	391,094	337,143	53,951
NCFI ($)*	1.032	0.669	0.363	1.119	0.726	0.392
DEP ($)*	155,224	58,422	96,802	256,243	68,951	187,292
ACRES*	36,495	20,519	15,976	61,364	27,209	34,155
MTR (ratio)	963	911	51	534	313	221
ENTROPY (index)	0.176	0.189	-0.013	0.183	0.159	0.024
WC($)*	0.169	0.204	-0.035	0.051	0.085	-0.034
Intrate (ratio)	138,332	101,058	37,274	387,571	48,163	339,407
OFFI (thousand $)	0.0438	0.0792	-0.0354	0.0485	0.0790	-0.0305
I($)	76.647	57.401	19.246	98.238	68.017	30.221

Table 47: Average Value of Model Variables in 1996 and 2013 for Resident Livestock Farms

	Livestock Farm		
Variable (units)	2013	1996	Change
I ($) [A]	15,259	38,357	-23,099
I ($) [B]	17,939	20,916	-2,977
K ($) [A]	459,101	555,166	-96,065
K ($) [B]	259,549	272,459	-12,911
Prindex (index)	1.116	0.785	0.331
NCFI ($)*	85,757	98,043	12,286
DEP ($)*	27,421	34,328	-6,907
ACRES*	160	253	93
MTR (ratio)	0.149	0.154	-0.005
ENTROPY (index)	0.098	0.086	0.013
WC ($)*	63,158	87,896	-24,738
Intrate (ratio)	0.0453	0.0787	-0.0334
OFFI (thousand $)	74.311	56.166	18.146

[A] does not include breeding livestock
[B] includes breeding livestock

Table 48: Average Value of Model Variables in 1996 vs. 2013 for Intermediate Grain and FNV Farms

	Grain Farm			FNV		
Variable (units)	2013	1996	Change	2013	1996	Change
I ($)	46,973	18,965	28,008	37,918	15,636	22,282
K ($)	415,333	319,319	96,013	450,673	342,380	108,293
PrIndex (index)	1.030	0.652	0.378	1.119	0.726	0.392
NCFI ($)*	155,224	43,965	111,259	188,881	74,465	114,417
DEP ($)*	36,495	20,526	15,969	47,221	28,333	18,888
ACRES*	963	933	29	412	313	98
MTR (ratio)	0.175	0.182	-0.006	0.170	0.173	-0.003
Entropy (index)	0.167	0.197	-0.030	0.052	0.076	-0.024
WC ($)*	143,135	85,432	57,703	394,684	47,866	346,818
Intrate (ratio)	0.0450	0.0793	-0.0343	0.0489	0.0791	-0.0301
OFFI (thousand $)	71.698	50.319	21.379	81.729	73.848	7.881

Table 49: Average Value of Model Variables in 1996 vs. 2013 for Intermediate Livestock Farms

	Livestock Farm		
Variable (units)	2013	1996	Change
I ($) [A]	14,358	38,031	-23,673
I ($) [B]	16,911	20,863	-3,952
K ($) [A]	441,180	568,321	-127,140
K ($) [B]	256,470	282,585	-26,116
Prindex (index)	1.106	0.782	0.324
NCFI ($)*	76,625	95,307	-18,683
DEP ($)*	25,051	34,918	-9,866
ACRES*	166	286	-120
MTR (ratio)	0.000	0.150	-0.150
ENTROPY (index)	0.109	0.083	0.026
WC ($)*	69,383	88,412	-19,028
Intrate (ratio)	0.0453	0.0787	-0.0334
OFFI (thousand $)	69.496	50.590	18.906

[A] does not include breeding livestock
[B] includes breeding livestock

Compared to 1996 and earlier years, by 2013 grain and FNV farms experienced large increases in the average level of capital investment, farm stock capital levels, agricultural output prices, net cash farm incomes, depreciation tax expenses and working capital levels. Resident and Intermediate livestock farms, while seeing increases in average output prices in 2013 compared to 1996, reduced investment and saw capital stock levels decline in comparison to prior years (when not accounting for breeding livestock). This was accompanied by lower net farm incomes, depreciation tax expenses, and working capital levels in 2013 vs. 1996. Commercial livestock farms also reduced capital investment (not including breeding livestock) in 2013 vs. 1996 despite modest increases in net farm income and working capital levels. When breeding livestock is included in the definition of investment and farm capital stock, average livestock farm investment and capital stock levels are higher 2013 vs. 1996. This statistic indicates that in 2013 vs. 1996 livestock farms shifted total investment away from machinery and equipment and towards greater investment in breeding livestock.

9.1.2 Methodology

To estimate the change in average farm investment between 2013 vs. 1996 I first multiply the difference in the average level of the independent variables between these two years (calculated in tables A24A-C) by the estimated coefficient[18]. Since the dependent variable in the model is the rate of investment, or dollars invested per dollars of capital stock, the result is the difference in the rate of investment in 2013 vs 1996. To express this difference in dollars of capital invested, I multiply by the average level of capital stock over the sample time period[19]. This is done separately for each farm typology and farm enterprise type. The total change in investment explained by changes in the model variables between 2013 and 1996 is calculated as the sum of the changes in investment predicted by each of the independent variables separately. The residual is calculated as the actual change in investment between 1996 and 2013 less the total change in investment explained by changes in the model variables.

---

[18] This can be expressed as: $I_{C,2013}$-$I_{C,1996}$ $=\sum B_k[X_{2013,k}$-$X_{1996,k}] + [\, e_{2013}$-$e_{1996}]$, where I_{2013} and I_{1996} denote the average value of investment in 2013 and 1996, $X_{2013,k}$ and $X_{1996,k}$ the average value of each of the K independent variables (including the time dummy for 2013 and that for 1996) in 2013 and 1996, and e_{2013} and e_{1996} the error term in 2013 and 1996. The difference in investment is the sum of the difference in each of the model variables times the estimated coefficient plus the difference in the error terms between the two periods. All fixed effects terms or typology dummy variables present in the original regression specification are removed by taking the difference between two time periods.

[19] This is an approximation. The true difference in the rate of investment is I_{2013}-I_{1996} $= \frac{\widehat{I_{2013}}}{K_{c,2013}}$ - $\frac{\widehat{I_{c,1996}}}{K_{c1996}}$. Instead this is proxied by I_{2013}-$I_{1996} = \frac{I_{c,2013}-I_{c,1996}}{\bar{K}}$ where $\bar{K}$ is the average level of capital stock. The residual now includes differences in the rates of investment between 2013 and 1996 due to changes in the level of capital stock not accounted for by the model variables.

9.1.3 Investment Changes Explained

Figure 17, Figure 18, and Figure 19 show the estimated change in average farm capital investment between 2013 vs. 1996 explained by changes in each variable in the model separately for commercial, resident and intermediate farms respectively. Figure 20, Figure 21, and Figure 22 compare the total change in investment explained by changes in the model variables with that not explained by the model variables for commercial, resident and intermediate farms.

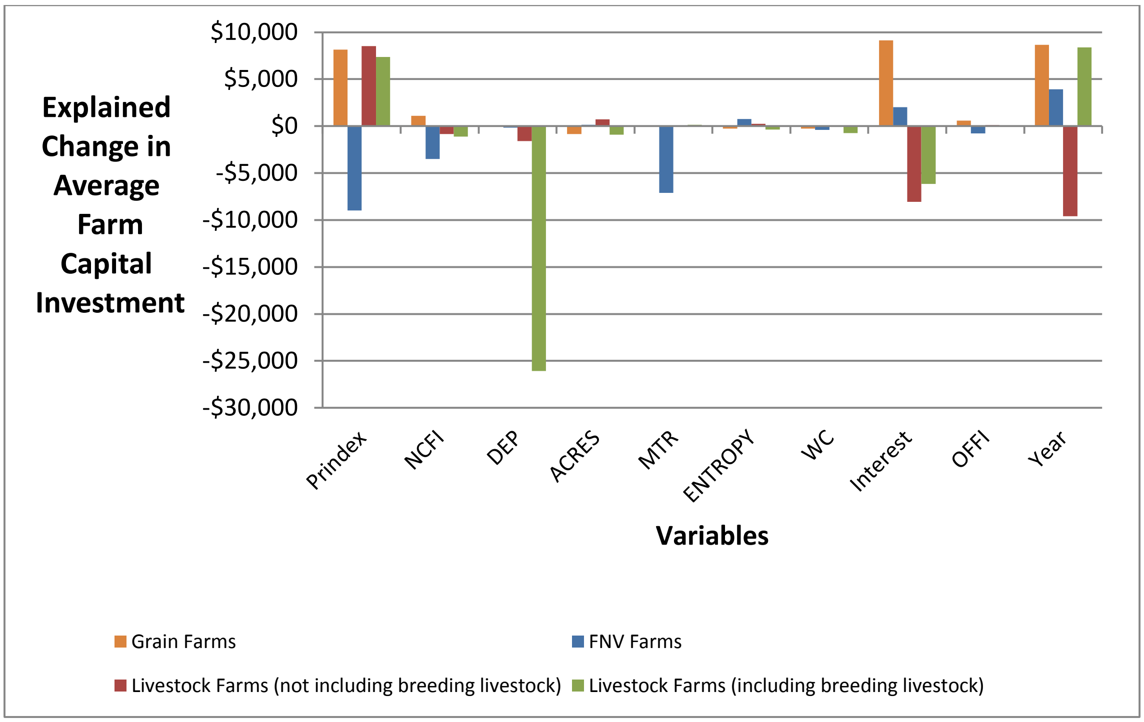

Figure 17: Change in Average Annual Farm Capital Investment in 2013 vs. 1996 Explained by Changes in Each of the Variables Separately for Commercial Farms by Farm Production Type

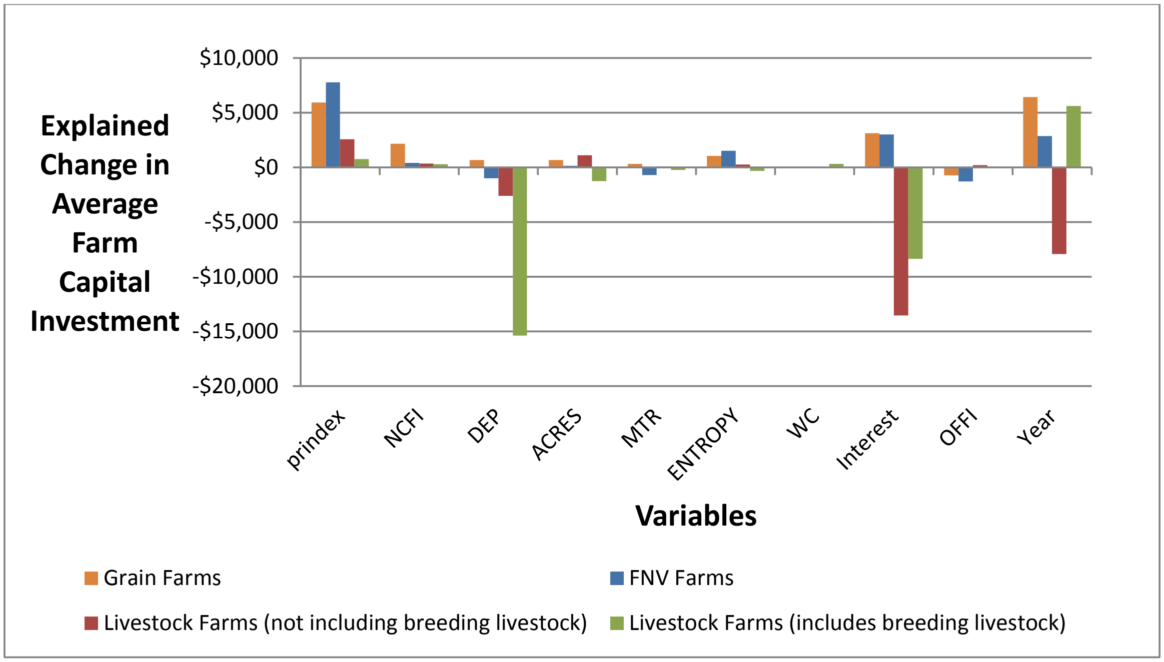

Figure 18: Change in Average Annual Farm Capital Investment in 2013 vs. 1996 Explained by Changes in Each of the Variables Separately for Resident Farms by Farm Production Type

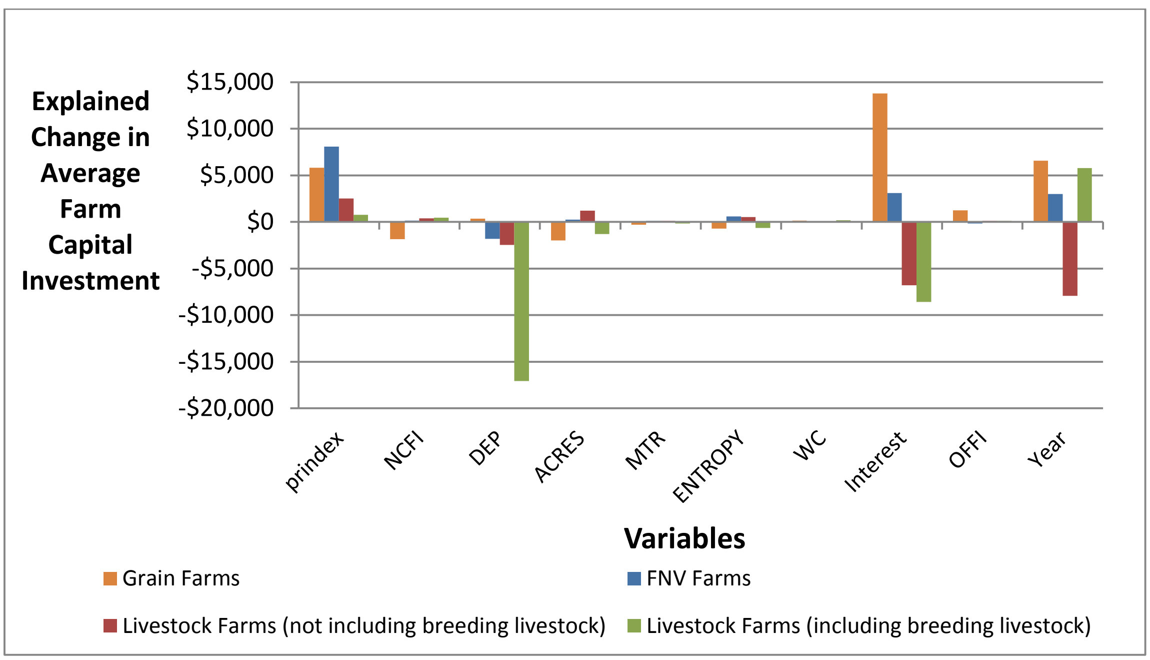

Figure 19: Change in Average Annual Farm Capital Investment in 2013 vs. 1996 Explained by Changes in Each of the Variables Separately Intermediate Farms by Farm Production Type

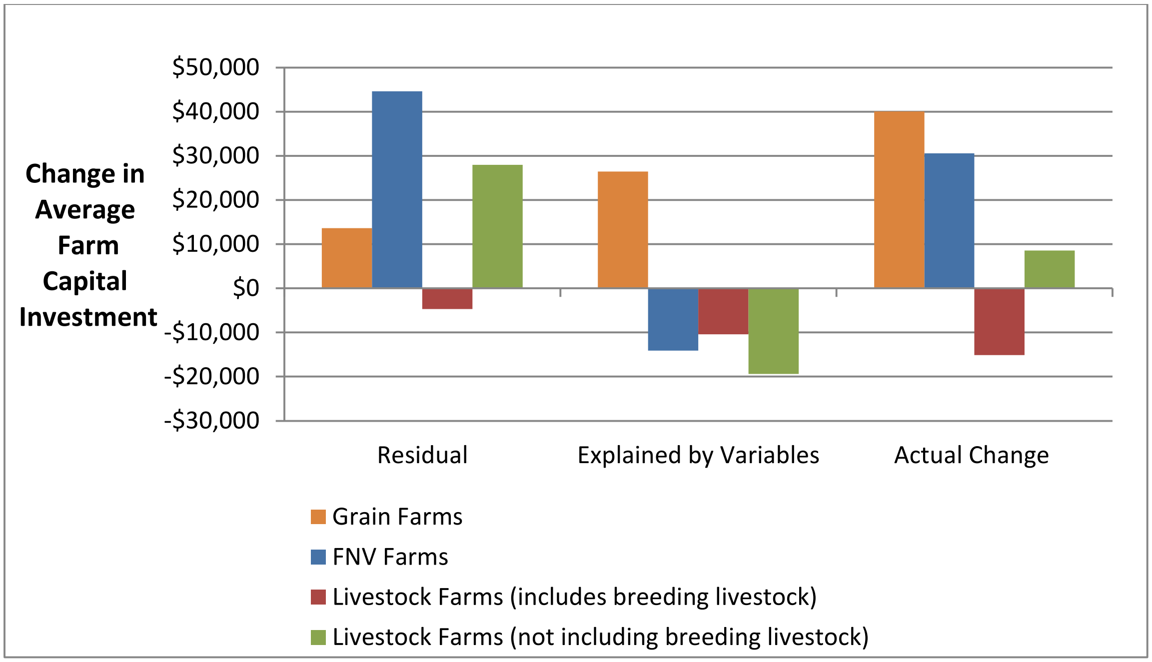

Figure 20: Total change in annual farm capital investment explained by changes in model variables in 2013 vs. 1996 for Commercial Farms by Farm Production Type

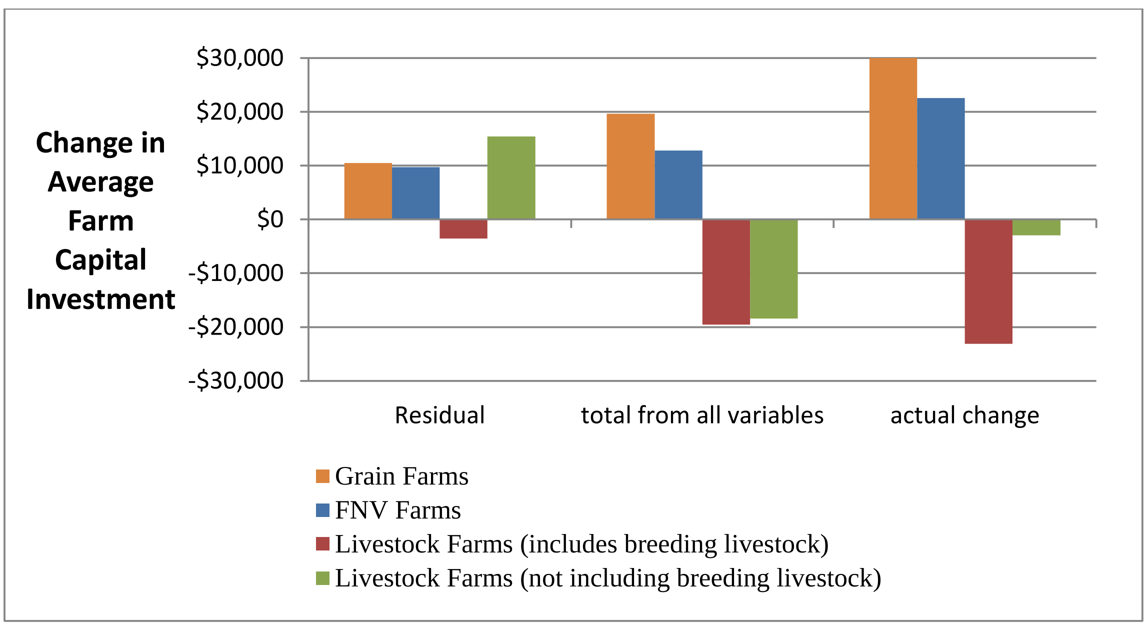

Figure 21: Total Change in Annual Farm Capital Investment Explained by Changes in Model Variables in 2013 vs. 1996 for Resident Farms by Farm Production Type

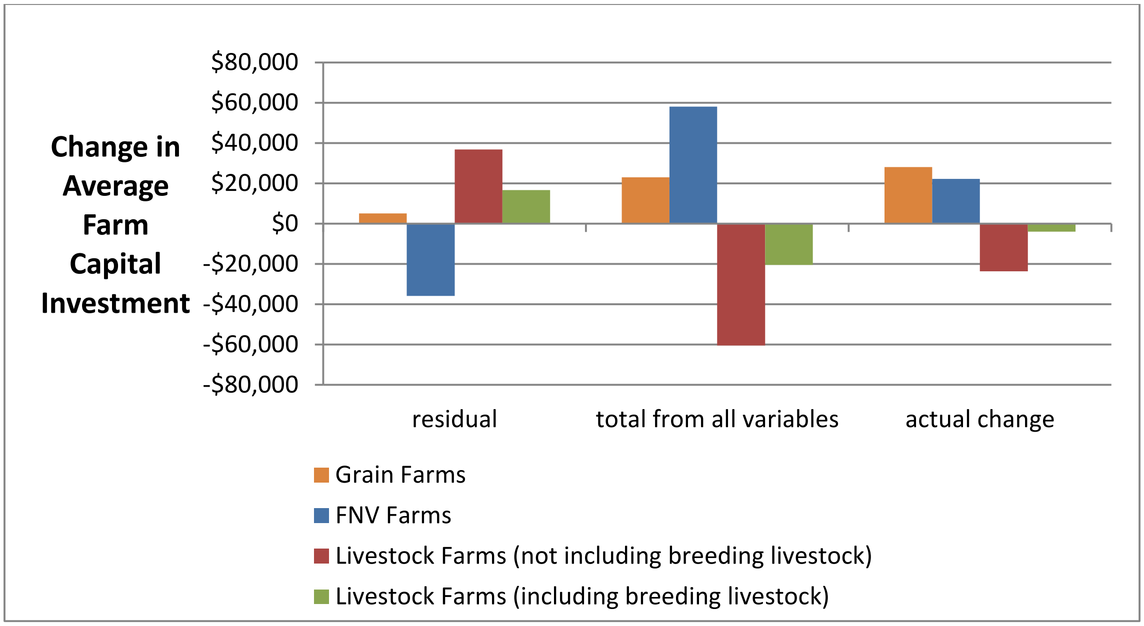

Figure 22: Total Change in Annual Farm Capital Investment Explained by Changes in Model Variables in 2013 vs. 1996 for Intermediate Farms by Farm Production Type

Changes in model variables are able to explain the majority of the increase in investment for grain and livestock farms (when breeding livestock is excluded) between 2013 and 1996. Of the change in average commercial grain farm investment between these years, $34,399, or 85%, of the increase is in commercial grain farm investment and $10,170, or 65%, of the decrease in commercial livestock farm investment is accounted for by changes in the model variables. Changes in the model variables between 1996 and 2013 do a poor job explaining changes in average farm investment for commercial FNV farms and commercial livestock farms (including breeding livestock). The estimated coefficients and changes in the model variables indicate that average farm capital investment should be lower in 2013 vs. 1996 for commercial FNV farms and commercial livestock farms (including breeding livestock). Instead, both are larger in 2013 vs. 1996. These differences can be accounted for by large negative estimated coefficient values on output prices for FNV farms and depreciation expenses for livestock farms (including breeding livestock).

The majority of the difference between 2013 and 1996 average farm capital investment levels on commercial grain and livestock farms in 2013 vs. 1996 can be explained by increases in output prices, decreases in interest rates, and 2013 year dummy variables. Changes in output prices, interest rates, and other factors specific to 2013 explain $10,600, $11,887 and $11,235 of the increase in average farm investment levels on commercial grain farms in 2013 vs. 1996. Reductions in interest rates and the 2013 year dummy variable explains $7,881 and $9,367 of the decrease in average investment levels on commercial livestock farms. Increases in output prices, all else held constant, indicate that commercial livestock farm capital investment should be $8,037 higher in 2013 vs. 1996. The year dummy variable represents factors unique to 2013 but common across all farm production types and typologies and not accounted for by specific variables within the model. These could include weather conditions and changes in export demand.

A smaller portion of the difference in commercial farm investment between these two years can also be explained by changes in net farm income, off-farm income, acres, and depreciation tax expenses. Changes in net farm income explain $1,437 of the increase in investment for commercial grain farms and $818 of the decrease in investment for commercial livestock farms. For commercial farms, an increase in average off-farm income levels explains $783 of the increase in average farm investment while a decrease in average farm acreage would predicts a $1,086 decrease in investment. For commercial livestock farms, the decline in tax depreciation expenses in 2013 compared to 1996 explains $1,571 of the decline in investment, while the increase in average farm acreage leads to an estimated $400 increase in average farm capital investment in 2013 vs. 1996.

Similar results are obtained for resident and intermediate farms. The model does an adequate job at explaining resident and intermediate grain and livestock (not including breeding livestock) average farm capital investment. Differences in the average level of the model variables in 2013 vs. 1996 explain 75% and 91% of difference in average resident and intermediate grain farm investment and 78% and 46% of resident and intermediate livestock farm investment. The model does an adequate job of estimating changes in resident and intermediate FNV farms, while it performed poorly for commercial FNV farms. Differences in the average value of the model variables in 2013 vs. 1996 explain 54% of the difference in average resident FNV farm capital investment levels and 63% of intermediate FNV farm capital investment. This is largely explained by the positive coefficient on output prices for resident and intermediate FNV farms compared to the negative coefficient on output prices for commercial FNV farms. The livestock model (including breeding livestock) does equally as poor a job estimating investment changes between 1996 and 2013 within the resident and intermediate farms as for the commercial farms. This leads me to believe that there is something specifically driving breeding livestock investment, common across all farm typologies, which my model is not capturing.

Similar to commercial farms, increases in output prices, falling interest rates, and the 2013 year dummy variable explain the majority of the change in in resident and intermediate grain farm capital investment. Differences include the greater impact of: net cash farm income on resident grain farm investment, off-farm income levels on intermediate grain farms, and reductions in tax depreciation expenses on resident and intermediate livestock farms. Increases in average grain net farm incomes explains $2,499 of the increase in resident grain farm investment and only $1,105 of the increase in commercial grain farm investment. Higher average off-farm income in 2013 vs. 1996 accounts for $1,240 of the increase in intermediate grain farm investment compared to $603 for commercial grain farms. The reduction in average depreciation expenses per unit capital stock explains $2,596 of the decrease in resident livestock investment and $2,483 for intermediate livestock farm investment. This is in contrast to the $1609 decrease in investment on commercial livestock farms explained by decreases in depreciation per unit capital stock.

9.2 What Does this Mean for Farm Investment in 2024?

Farm capital investment declined as of 2015 given lower output prices and net farm incomes between 2013 and 2015. The level of farm debt has begun to rise. After years of constant or declining interest rates, the Federal Reserve raised bank lending interest rates for the first time in December 2015. These trends are projected to continue for the next few years. Given each of these has an impact on farm capital investment, one interesting question is what will average farm capital investment look like in 2024 given the expected changes in economic conditions between now and then?

To answer this question, in the next section I utilize my model to estimate future changes in investment over the 2014-2024 time period given projected changes in output prices, net farm income, tax depreciation levels, marginal tax rates, working capital levels, and interest rates. I utilize the estimated grain and livestock (not including breeding livestock) investment models only. I do not use the FNV and livestock (including breeding livestock) investment models given their lower ability to accurately estimate changes in investment over the sample period.

9.2.1 Projection Data 2014-2024

Projected changes in output prices for crop and livestock farms, net farm incomes, and interest rates are estimated using data from the Food and Agriculture Policy Research Institute (FAPRI)[20] 10-year baseline estimates. For changes in crop and livestock output prices, I utilize the FAPRI estimates for annual gross crop and livestock receipts. For changes in net farm income I use the FAPRI projections for net farm income earned by the agricultural sector. Changes in interest rates are represented as one third the projected change in prime interest rates. FAPRI nominal crop receipts, livestock receipts, and net farm incomes were converted to real net farm incomes using the FAPRI CPI estimates. This is in order to be consistent with my model, which uses real output and net farm income levels. Estimates of annual changes in tax depreciation expenses, marginal tax rates, and working capital levels are my best estimates.

Figure 23 shows the calculated annual continuous percentage change in each of these variables.

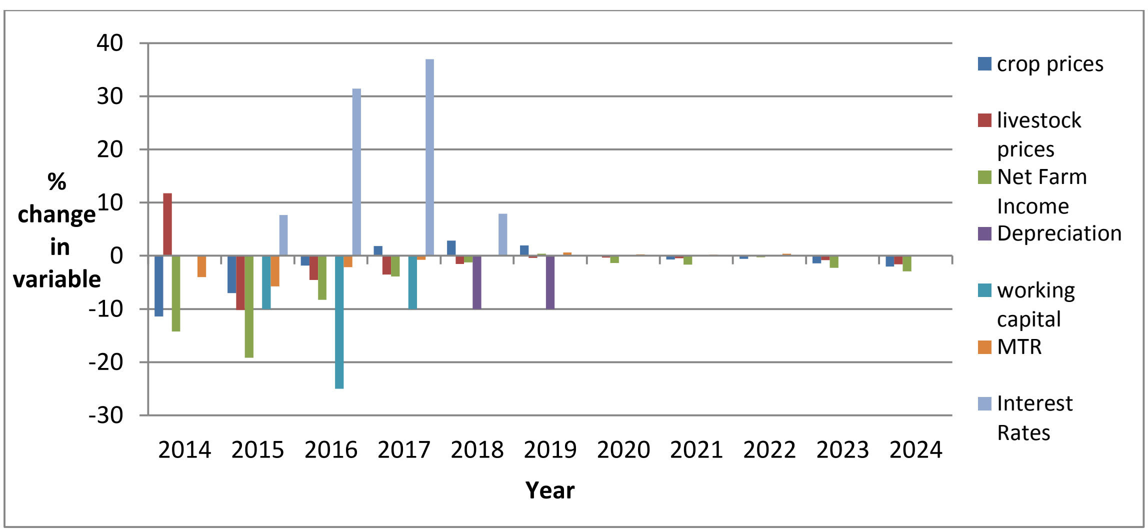

Figure 23: Projected Annual Change in Model Variables 2014-2023

[20]Excel files with FAPRI data can be obtained at: http://www.fapri.missouri.edu/publication/2015-u-s-baseline-briefing-book/?preview=true

Grain farm real output prices decrease 12% in 2014, 7% in 2015 and 2% in 2016. Livestock prices increase by 11% in 2014 but then decrease by 11% in 2015, 5% in 2016 and 4% in 2017. For the remainder of the 2018-2024 time period crop and livestock prices are projected to remain close to these new 2017 levels, either increasing or decreasing by 0-3% annually. Real net farm income levels will drop severely between 2014 and 2017. Net Farm incomes fall by 15% in 2014, 21% in 2014, 9% in 2016 and 4% in 2017. For the rest of the time period, nominal net cash farm income continues to increase slightly, but less than inflation leading to decreases in real cash farm income of between 1-3% over the 2018-2024 time period.

I assume that the current depreciation tax laws remain intact until 2018, and hence there is no change in the average rate of tax depreciation per unit capital until 2018. This is based on the "Protecting Americans from Tax Hikes Act of 2015**" (**PATH Act**)** passed on December 18, 2015 (Gearhardt, January 2016). Under this act, the Section 179 depreciation expensing limit for new capital purchase was extended indefinitely at its current value. The current bonus depreciation percentage limit was extended at its current 50% level though 2017, after which it decreases to 40% in 2018 and 30% in 2019. To account for these declines I estimate a 10% reduction in the rate of tax depreciation each of these years. I assume that bonus depreciation remains constant at 30% after this point, leading to no change in tax depreciation expenses beyond 2019. These projections assume that rules governing current depreciation tax lives and normal deduction percentages remain consistent at their 2013 levels.

I estimate the projected annual rate of change in marginal tax rates as one-third of the annual percentage change in net cash farm income each year. The smaller reduction in tax rates compared to that of farm income takes into account that the model estimates a federal tax rate using total household income. Reductions in total household income may be less than the reduction in farm incomes depending on levels of off-farm income and other taxable income sources and actions on the part of the household. These estimates assume that federal tax rates, standardized and itemized deduction levels, and the rates and limits for individual tax line items remain at their 2013 levels.

I estimate a 10% decline in working capital in 2014, a 25% decline in 2015, and an additional 10% decline in 2016. These estimates are based upon documented increases in farm debt levels and declines in farm asset levels in 2014 and 2015 (USDA, November 2015) and my expectations that this pattern will continue in 2016 given further expected declines in farm income levels. After 2016, I assume that working capital remains constant at its 2017 level as farm incomes stabilize.

9.2.2 Methodology

I calculate the projected change in average farm capital investment due to changes in each variable separately within farm types and typologies. First I calculate the total percentage change in each variable between 2014-2024. This is done by taking the sum of the annual continuous percentage changes in the variable over these years. This is then multiplied by the partial investment elasticity. This results in an estimate of the average change in farm capital investment in 2024 compared to 2013 given a change in the specified variable.

9.2.3 Projected Change in Investment

The results are summarized in table 50 for grain farms and table 51 for livestock farms.

Table 50: Projected Change in Average Farm Investment in 2024 vs. 2013 for Grain Farms

Variable		**Resulting Change ($) in Average Farm Investment in 2024^{A} vs. 2013^{B}**		
Variable Name	Change (%)	Commercial Farms	Resident Farms	Intermediate Farms
Output Prices ^{D}	-19	-2,879***	-2,075*	850
Net Farm Income ^{D}	-59	-8,815**	728	1,129
Tax Depreciation	-26	-336	-2,517	-1,391
Working Capital	-50	545	276	390
MTR	-11	4,534**	-949	-400
Total (before Interest Rates)		-7,218	-4,537	577
Interest Rates	25	-4,576	-3,365	-3,448
Total (including interest rates)		-11,794	-7,903	-2,872

Table 51: Projected Change in Average Farm Investment in 2024 vs. 2013 for Livestock Farms

Variable		**Resulting Change ($) in Average Farm Investment in 2024^{A} vs. 2013^{C}**		
Variable Name	Change (%)	Commercial Farms	Resident Farms	Intermediate Farms
Output Prices	-13	-2,683***	-787	-1,308*
Net Farm Income	-59	-4,414	-41	-645
Tax Depreciation	-26	-2,593	-1,909***	-377

Table 51: Continued

Working Capital	-50	-610	-116	-267
MTR	-11	344	338	1,730
Total (before Interest Rates)		-9,955	-2,515	-876
Interest Rates	25	4,215	3,491	3,500
Total (including interest rates)		-5,740	975	2,624

[A] These are the reduction in average farm capital investment in 2024 given the state change in that variable and all else held constant. Stars indicate statistical significance of partial investment elasticities used in calculations with [d] Statistical significance: *= 90% Confidence level, **=95% confidence level, ***=99% confidence level.
[B] The 2013 average grain farm investment levels are: $74,717 for commercial farms, $48,046 for Resident Farms, $46,972 for Intermediate farms
[C] The 2013 average livestock farm investment levels (not including breeding livestock) are: $26,121 for commercial farms, $15,258 for Resident Farms, $14,358 for Intermediate farms
[D] Expected Changes in Real Dollar Values.

Given the projected change output prices, net farm incomes, marginal tax rates, depreciation tax rates and working capital levels, average farm capital investment is expected to decline for all but intermediate grain farms. The largest decline in investment occurs on commercial grain and livestock farms. Average farm capital investment will decline by $7,218 on grain commercial grain farms and by $9,955 on commercial livestock farms. Resident farm investment will fall significantly as well. Resident grain farm investment will be $4,537 lower for grain farms and $2,515 lower for livestock farms in 2024 compared to 2013. Intermediate farm investment is the least impacted given projected changes in model variables. When projected changes in interest rates are included in the total projected change, the decline in farm capital investment is larger across all farm typologies.

The largest decline in commercial farm capital investment arises due to falling farm income levels. A projected 59% decrease in real net cash farm results in an $8,815 decrease in average commercial grain farm investment and a $4,414 decrease in average livestock farm investment. The second largest decline in commercial farm investment is due to increasing interest rates. Other important impacts on commercial farm investment include a $4,534 increase in commercial grain farm investment due to a decline in marginal tax rates, an average $2,879 increase in commercial grain farm investment levels due to falling output prices, and a $2,683 decline in commercial livestock investment due to a decline in output prices.

For resident grain farms and intermediate livestock farms falling output prices have a significant and larger impact on overall average farm investment relative to declines in net farm income. Falling output prices reduces resident grain farm investment by $2,075 and intermediate livestock farm investment by $1,308. Also, projected future declines in depreciation expenses will have the largest impact on resident farms and commercial crop farms.   A projected 26% decrease in tax depreciation expenses results in a decrease in average farm capital investment of $2,031 for commercial livestock farms, $1,971 for resident grain farms and $1,029 for resident livestock farms.

CHAPTER 10: CONCLUSIONS AND FUTURE STEPS

Below I summarize the research undertaken, draw conclusions and outline future steps.

10.1 Summary

In this study, I examine U.S. farm expenditures on machinery, equipment and structures by farm enterprise type and farm typology, a classification of farms based on farm income and primary occupation of the operator. The dataset utilized consists of constructed synthetic panels from annual cross sectional farm level observations from the Agricultural Resource Management Survey (ARMS) data for survey years 1996-2013. Regressions are estimated separately for 1) grain 2) fruit, nut and vegetable (FNV), and 3) livestock farms. Using these results, I am able to test three hypothesis regarding the difference in marginal responses between farm typologies given changes in output prices, returns, tax policy variables, and liquidity levels. The estimated model is then used to estimate the change in investment levels in 2013 vs 1996 explained by changes in the model variables over this time period. Finally, I calculate the expected change in average farm capital investment levels in 2024 compared to 2013 given projected changes in key model variables.

10.2 Conclusions

Commercial farm investment responds to changes in output prices, net farm income, marginal tax rates, depreciation tax rates, and acres, though the magnitude and statistical significance of these impacts differ by farm production type. I can accept my first hypothesis, that commercial farm investment is more responsive to changes in output prices and returns compared to intermediate farms for commercial grain farms only. I can accept this hypothesis with regards to returns for FNV farms but not for output prices. I can accept my second hypothesis, that resident farms are more sensitive to tax policy variables compared to commercial farms, for grain farms with regards to marginal tax rates and for livestock farms with regards to tax depreciation expense rates. I can accept the third hypothesis, that intermediate farms exhibit credit constrained behavior and increase investment to a greater degree compared to commercial and resident farms given increases in farm liquidity, for FNV farms, but not for grain or livestock farms.

Changes in output prices, interest rates, and year specific impacts explain the majority of the difference in average grain and livestock farm investment levels in 2013 compared to 1996. Within individual farm typologies, a large portion of the increase in average investment levels on commercial farms between these years is explained by higher returns in 2013 compared to 1996. For resident and commercial livestock farms declines in the average tax depreciation expense rate explain a significant portion of the change in investment between these years. Calculating projected average farm capital investment in 2024 given expected changes in key variables over the 2014 to 2024 time period highlights the importance of the following: net farm income levels and marginal tax rates on projected commercial farm investment, changes in tax depreciation policy on resident and commercial livestock farm and resident grain farm investment, and livestock output prices for intermediate livestock farm investment.

My research both sheds light on the differential impacts of changes in the factors driving the demand for investment across different farm typologies as well as the importance of accounting for both microeconomic and macroeconomic factors when estimating projected agricultural investment. The literature on agricultural investment has tended to put a large emphasis on microeconomic factors, such as prices and returns, while placing a smaller emphasis on macroeconomic factors. My analysis indicates that macroeconomic factors may have an equally as important impact as microeconomic factors on determining farm capital investment. In this light, upcoming anticipated changes in the interest rate may have significant impacts on farm investment, both to the degree to which proposed changes in interest rates set by the Federal Reserve impact farm loan rates and the cost of borrowing money, as well as the degree to which changes in interest rates impact exchange rates, the value of the dollar, and agricultural commodity prices and export/import levels. Given the current lackluster economic activity in Europe and Asia and a dearth of high yielding alternative investment options, the

Federal Reserve's proposed actions may have little impact on actual loan rates and/or the value of the dollar. In that case, there would be little impact on farm capital investment from changes in the Federal Reserve loan rates. On the other hand, if these measures are successful and lead to both an increase in interest rates and trigger an appreciation of the dollar, leading to lower agricultural export demand and falling net farm incomes, declines in investment may be even more severe than anticipated.

10.3 Future Steps

Further work is needed in this area. While interest rates explain a large portion of the change in investment (2013 vs. 1996) and are projected to have a strong impact on future farm investment, the coefficients are statistically insignificant. This could be due to either: the measurement I use for interest rates, the use of a fixed effects model, or the use of pseudo panels. Future work in this area may involve finding data for or calculating average interest rates at the state and production type level, or constructing a measure of farm interest expenses paid on current farm loans which takes into account both the large number of farms with no current interest rate expenses and addresses issues of multicollinearity between farm size, investment levels, net farm income levels, and total interest rate expenditures.

The above step would correspond with another step I plan to undertake, which is the creation of an input cost index. Such an index would allow me to examine the impact of changes in input costs on farm investment demand. It may also shed additional light on the large portion of the difference in investment in 2013 vs. 1996 explained by the dummy year variable in the model. Important relationships to model using this index include investment and energy and variable input prices on grain farms, labor prices on FNV and livestock farms, and feed costs for livestock and dairy farms.

In conjunction, the measure of working capital I use needs to be updated to account for raised breeding livestock. This involves returning to the original survey dataset and re-creating the pseudo panel datasets. This is something that I am unable to do currently. This may shed greater light on the factors driving livestock investment as well differences between the investment behavior within livestock vs. grain farm investment. Knowing these differences is key when looking to meet the investment demand for producers within these different sectors.

Finally, I can utilize the alternative pseudo panels I created to see if my results differ utilizing interaction terms based upon farm size or asset value levels. In particular, this would allow me to further examine the impact of changes in working capital and debts on farm investment. This would also allow for further analysis of the impact of farm size on investment. By separating resident farms within this sample, I may be able to obtain more finite results for intermediate farms than I currently have been able to within my sample. These additional results will be invaluable as the agricultural sector seeks to understand, anticipate and plan for changes in future farm capital investment in a period of declining farm prices and incomes.

LIST OF REFERENCES

LIST OF REFERENCES

Abebe, Kassahun, Dale C. Dahl, and Kent Olson. “The Demand for Farm Machinery”. No. 14194. University of Minnesota, Department of Applied Economics, 1989.

Ariyaratne, Chatura B., and Allen M. Featherstone. "Impact of government payments, depreciation and inflation on investment behavior in American agriculture sector using sample of Kansas farms." In *AAEA Meetings, Milwaukee, WI* (2009) available at: http://ageconsearch. umn.edu/bitstream/20374/1/sp04mi01.pdf (accessed 1 January 2015). 2009

Barry, Peter J., Ralph W. Bierlen, and Narda L. Sotomayor. "Financial structure of farm businesses under imperfect capital markets." *American Journal of Agricultural Economics* 82, no. 4 (2000): 920-933.

Baum, Christopher F. "Residual diagnostics for cross-section time series regression models." *The Stata Journal* 1, no. 1 (2001): 101-104.

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

Bierlen, Ralph, and Allen M. Featherstone. “Fundamental Q, cash flow, and investment: evidence from farm panel data.” *The Review of Economics and Statistics* (1998): 427–35.

Blank, Steven C., et al. "Agricultural profits and farm household wealth." *American journal of agricultural economics* 86, no. 5 (2004): 1299-1307.

Board of Governors Federal Reserve System Agricultural Finance Databook. “Regional disaggregation of survey results” tables for years 2003, 2007, 2010, 2013 Available at: http://www.federalreserve.gov/releases/e15/current/pdf/databook.pdf (accessed 4 August 2014).

Boetel, Brenda L., Ruben Hoffmann, and Donald J. Liu. "Estimating investment rigidity within a threshold regression framework: the case of US hog production sector." *American Journal of Agricultural Economics* 89, no. 1 (2007): 36-51.

Bokusheva, Raushan, Vladislav Valentinov, and Viktoriya Anpilogova. "The investment behavior of Russian Farms." *Post-Communist Economies* 19, no 1 (2007): 53-71.

Cameron, Adrian Colin, and Pravin K. Trivedi. *Microeconometrics using stata*. (2010): 166.

Conway, Roger K., James Hrubovcak, and Michael R. LeBlanc. *A forecast evaluation of capital investment in agriculture*. No. 1732. US Department of Agriculture, Economic Research Service, 1987.

Cromarty, William A. "The farm demand for tractors, machinery and trucks." *Journal of Farm Economics* 41, no 2 (1959): 323-331.

Deaton, Angus. "Panel data from time series of cross-sections." *Journal of econometrics* 30, no. 1 (1985): 109-126.

Dubman, Robert. "Variance estimation with USDA‘s farm costs and returns surveys and agricultural resource management study surveys” (2000).

Durst, Ron. "Federal tax policies and farm households." *Economic Information Bulletin* 54, (2009).

ERS USDA website. “ARMS farm financial and drop production practices. Documentation” available at: http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation.aspx (accessed 5 December 2014)

Fazzari, Steven M., et al. "Financing constraints and corporate investment." *Brookings papers on economic activity* 1988, no 1 (1988): 141-206.

Featherstone, Allen M., Timothy A. Park, and Jeremy G. Weber. "Keeping ARMS relevant: extracting additional information from ARMS." *Agricultural Finance Review* 72, no. 2 (2012): 233-246.

Food and Agricultural Policy Research Institute, University of Missouri. "2015 U.S. Baseline Briefing Book". Available at: APRI http://www.fapri.missouri.edu/publication/2015-u-s-baseline-briefing-book/?preview=true.pdf (accessed January 2015).

Girao, Jose A., William G. Tomek, and Timothy D. Mount. "The effect of income instability on farmers' consumption and investment." *The Review of Economics and Statistics* 56, no 2 (1974): 141-149.

Gilchrist, Simon, and Charles P. Himmelberg. "Evidence on the role of cash flow for investment." *Journal of monetary Economics* 36, no 3 (1995): 541-572.

Gustafson, Cole R., Peter J. Barry, and Steven T. Sonka. "Machinery investment decisions: A simulated analysis for cash grain farms." *Western Journal of Agricultural Economics* (1988): 244-253.

Guastella, Gianni, et al. "CAP effects on agricultural investment demand in Europe." Book of Abstracts. 2013.

Hadrich, Joleen, Ryan Larsen, and Frayne E. Olson. "Impact of the Section 179 tax deduction on machinery investment." *Agricultural Finance Review* 73, no. 3 (2013): 458-468.

Hall, Robert E., and Dale W. Jorgenson. "Tax policy and investment behavior." *The American Economic Review* 57, no 3 (1967): 391-414.

Halvorsen, Robert. "The effects of tax policy on investment in agriculture." *The Review of Economics and Statistics* (1991): 393-400.

Hanson, Gregory D., and Diane R. Bertelsen. "Tax reform impacts on agricultural production and investment decisions." *American Journal of Agricultural Economics* 69, no 5 (1987): 1013-1020.

Hart, Chad E., and Sergio H. Lence. "Financial constraints and farm investment: A Bayesian examination." *Journal of Business & Economic Statistics* 22, no 1 (2004): 51-63.

Hoechle, Daniel. "Robust standard errors for panel regressions with cross-sectional dependence." *Stata Journal* 7, no. 3 (2007): 281.

Hoppe, Robert A. "Structure and finances of U.S. farms: family farm report, 2014 edition." *USDA-ERS Economic Information Bulletin* 132, (2014).

Hoppe, Robert A. and James M. MacDonald. "Updating the ERS farm typology." *USDA-ERS Economic Information Bulletin* 110, (2013).

Hoppe, Robert A. "Profit margins increase with farm size." Amber Waves. USDA. February 2, 2015, available at: http://www.ers.usda.gov/amber-waves/2015-januaryfebruary/profit-margin-increases-with-farm-size.aspx (accessed November 2015).

Hubbard, R. Glenn, and Anil Kashyap. "Internal net worth and the investment process: An application to US agriculture." No. w3339. National Bureau of Economic Research, 1990.

Hüttel, Silke, Oliver Mußhoff, and Martin Odening. "Investment reluctance: irreversibility or imperfect capital markets?" *European Review of Agricultural Economics* 37, no 1 (2010): 51-76.

Internal Revenue Service. Various tax publications for years 1996-2013. Available at https://www.irs.gov/Forms-&-Pubs (accessed October 2014).

Jensen, Farrell E., John S. Lawson, and Larry N. Langemeier. "Agricultural investment and internal cash flow variables." *Review of Agricultural Economics*, 15, no. 2 (1993): 295–306.

Jorgenson, Dale W. "Capital theory and investment behavior." *The American Economic Review* 53, no 2 (1963): 247-259.

Jorgenson, Dale W., and Calvin D. Siebert. "A comparison of alternative theories of corporate investment behavior." *The American Economic Review* 58, no 4 (1968): 681-712.

Koksal, Aycan, and Michael Wohlgenant. "Alcoholic beverages and cigarettes: complements or substitutes? A pseudo panel approach." In *Southern Agricultural Economics Association 2011 Annual Meeting, February*, pp. 5-8. 2011.

Kolajo, Ebenezer F., and John L. Adrian. "Structural Analysis of Farm Machinery Demand in the United States." *North Central Journal of Agricultural Economics* (1986): 283-293.

Kuethe, Todd and Mitch Morehart. "The Agricultural Resource Management Survey." *Agricultural Finance Review 72 (2): 191-200.*

LeBlanc, Michael, and James Hrubovcak. "The effects of tax policy on aggregate agricultural investment." *American Journal of Agricultural Economics* 68, no 4 (1986): 767-777.

LeBlanc, Michael, James Hrubovcak, Ron Durst, and Roger Conway. "Farm machinery investment and the Tax Reform Act of 1986." *Journal of Agricultural and Resource Economics* 17, no. 1 (1992): 66–79.

Lopez, Ramon E. "The structure of production and the derived demand for inputs in Canadian agriculture." *American Journal of Agricultural Economics* 62, no 1 (1980): 38-45.

MacDonald, James M., and William D. McBride. "The transformation of US livestock agriculture scale, efficiency, and risks." *Economic Information Bulletin* 43, (2009).

MacDonald, James, and Doris Newton. "Milk Production Continues Shifting to Large-Scale Farms." *Amber Waves* (2014): 1E.

MacDonald, James Michael, Penni Korb, and Robert A. Hoppe. "*Farm size and the organization of U.S. crop farming*." US Department of Agriculture, Economic Research Service, 2013.

Mauer, David C., and Steven H. Ott. "Investment under uncertainty: The case of replacement investment decisions." *Journal of Financial and Quantitative Analysis* 30, no 4 (1995): 581-605.

McKenzie, David J. "Asymptotic theory for heterogeneous dynamic pseudo-panels." *Journal of Econometrics* 120, no. 2 (2004): 235-262.

Micheels, Eric T., Ani L. Katchova, and P. Barry. "Machinery investment in Illinois: a study examining existing investment motivations." In *AAEA Annual Meeting, Denver, Colorado*, pp.1-17. 2004.

Moffitt, Robert. "Identification and estimation of dynamic models with a time series of repeated cross-sections." *Journal of Econometrics* 59, no 1 (1993): 99-123.

National Research Council. Understanding American agriculture: challenges for the Agricultural Resource Management Survey, National Academies Press (2008).

Noss, Amanda. “Household Income: 2013.” American Community Survey Briefs, September 2014, available at: http://www.census.gov/content/dam/Census/library/publications/2014/acs/acsbr13-02.pdf (accessed December 2015).

Gearhardt, Larry. “Section 179 changes under “protecting Americans from tax hikes” act.” Agricultural Law & Taxation, Ohio State University Extension. Available at: http://aglaw.osu.edu/blog/wed-01132016-856am/section-179-changes-under-protecting-americans-tax-hikes-act (Accessed January 2015).

O'Donoghue, Erik J., and James B. Whitaker. "Do direct payments distort producers' decisions? An examination of the Farm Security and Rural Investment Act of 2002." *Applied economic perspectives and policy* 32, No. 1 (2010): 170-193.

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

Russell, Jeffrey E., and John W. Fraas. "An application of panel regression to pseudo panel data." *Multiple linear regression viewpoints* 31, No. 1 (2005): 1-15.

Serra, Teresa, Spiro Stefanou, José M. Gil, and Allen Featherstone. "Investment rigidity and policy measures." *European Review of Agricultural Economics* 36, No. 1 (2009): 103-120.

Smith, Vincent H. "The effects of changes in the tax structure on agricultural asset replacement." *Journal of Agricultural and Applied Economics* 22.1 (1990): 113.

Sckokai, Paolo, and Daniele Moro. "Modeling the reforms of the common agricultural policy for arable crops under uncertainty." *American Journal of Agricultural Economics* 88.1 (2006): 43-56.

Trevena, Billy J., and Luther H. Keller. "Estimating the Investment Behavior of Farm Firms Using the Concept of Rational Distributed Lag Functions." *Southern Journal of Agricultural Economics* 6, no 1 (1974): 111-116.

USDA. (n.d.) "Farm income and wealth statistics, gross capital expenditures", available at: http://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/gross-capital-expenditures.aspx (accessed August 2015).

USDA. (n.d.) "Farm income and wealth statistics, gross capital expenditures", available at: http://www.ers.usda.gov/topics/farm-economy/farm-sector-income-finances/2015-farm-sector-income-forecast.aspx (accessed November 2015).

USDA. (n.d.) "ARMS farm financial and crop production practices: update and revision history", available at: http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/update-and-revision-history.aspx (accessed April 2016)

Vanzetti, David, and John C. Quiggin. "A comparative analysis of agricultural tractor investment models." *Australian Journal of Agricultural Economics* 29, no 2 (1985): 122-141.

Vasavada, Utpal, and Robert G. Chambers. "Investment in US agriculture." *American Journal of Agricultural Economics* 68, no.4 (1986): 950-960.

Verbeek, Marno, and Theo Nijman. "Minimum MSE estimation of a regression model with fixed effects from a series of cross-sections." *Journal of Econometrics*, Vol. 59, no. 1 (1993): 125-136.

Verbeek, Marno, and Francis Vella. "Estimating dynamic models from repeated cross-sections." *Journal of econometrics*, Vol. 127, no. 1 (2005): 83-102.

Vogel, Stephen and Sarah Low. "The Size and Scope of Locally Marketed Food Production." USDA. ERS, available at: http://www.ers.usda.gov/amber-waves/2015-januaryfebruary/the-size-and-scope-of-locally-marketed-food-production.aspx#.Vl4V2Ub08Sk (accessed December 2015).

Weber, Jeremy G., and Dawn Marie Clay. "Who does not respond to the Agricultural Resource Management Survey and does it matter?" *American journal of agricultural economics* (2013): aas171.

Weersink, Alfons J., and Loren W. Tauer. "Comparative analysis of investment models for New York dairy farms." *American Journal of Agricultural Economics* 71, no. 1 (1989): 136-146.

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

APPENDIX

APPENDIX: TABLES AND GRAPHS OF MODEL VARIABLES BY YEAR

Table 52 below provides a list of the mean, standard deviation, minimum and maximum value of the model variables within the pseudo panel dataset by year. The variables are: I=investment, K= capital stock, PrIndex=output price index, NCFI=net cash farm income, DEP=tax depreciation expenses, Acres= farm acres, Entropy= level of farm specialization, OFFI= off-farm income, WC= working capital, IR= interest rate. For additional information on their construction and what is included in each see the notes at the bottom of the table. Similar summary statistics for the sample as a whole are provided in the text in Table 12. These mean values of the sample observations by year are graphed in Figure 24-Figure 34.

Table 52*:* Summary Statistics for Pseudo Panel Dataset by Year

Variable	Mean	SD	Min	Max
Year= 1996				
I ($)	28,253	30,395	0	125,984
K ($)	364,127	248,813	23,813	1,092,475
PrIndex (index)	0.695	0.109	0.482	0.970
NCFI ($)	93,612	149,951	-32,580	769,389
DEP ($)	24,885	27,160	0	134,110
ACRES	687	1,432	7	13,919
MTR (rate)	0.237	0.052	0.000	0.388
ENTROPY (index)	0.117	0.089	0.000	0.391
OFFI ($)	58,257	49,335	-7,375	490,875
WC ($)	118,432	168,016	-292,613	994,078
IR (rate)	0.093	0.004	0.078	0.101
Year= 1997				
I	28,253	30,395	0	125,984
K	364,127	248,813	23,813	1,092,475
PrIndex	0.695	0.109	0.482	0.970
NCFI	93,612	149,951	-32,580	769,389
DEP	24,885	27,160	0	134,110
ACRES	687	1,432	7	13,919
MTR	0.237	0.052	0.000	0.388
ENTROPY	0.117	0.089	0.000	0.391
OFFI	58,257	49,335	-7,375	490,875
WC	118,432	168,016	-292,613	994,078
IR	0.093	0.004	0.078	0.101
Year= 1998				
I	33,506	52,088	0	431,971
K	411,194	347,036	19,864	2,7473,917

Table 52: Continued

PrIndex	0.660	0.137	0.373	0.983
NCFI	106,446	181,406	-92,758	1,088,136
DEP	32,208	42,139	0	122,321
ACRES	727	1,305	1	9,088
MTR	0.199	0.073	0.000	0.381
ENTROPY	0.110	0.088	0.000	0.380
OFFI	62,937	48,720	0.889	443,474
WC	142,229	234,296	-31,418	1,975,414
IR	0.092	0.003	0.083	0.097
Year= 1999				
I	29,272	33,407	0	187,055
K	410,198	292,990	22,356	1,325,851
PrIndex	0.620	0.147	0.335	0.984
NCFI	97,824	156,128	-57,662	767,296
DEP	29,461	26,540	0	196,017
ACRES	692	1,32	5	11,306
MTR	0.177	0.054	0.000	0.280
ENTROPY	0.107	0.084	0.000	0.357
OFFI	63,773	42,523	0	321,610
WC	133,143	179,253	-33,396	958,571
IR	0.091	0.003	0.038	0.098
Year= 2000				
I	31,781	40,432	0	233,124
K	454,915	669,134	25,988	1,192,236
PrIndex	0.657	0.153	0.329	1.029
NCFI	120,363	228,707	-32,341	4,980,959
DEP	30,347	43,097	0	324,090
ACRES	781	2,176	10	22,711
MTR	0.168	0.077	0.000	0.396
ENTROPY	0.108	.0084	0.000	0.362
OFFI	69,789	80,723	2,281	759,194
WC	212,302	1,007,624	-10,985	11,400,000
IR	0.097	0.004	0.092	0.107
Year= 2001				
I	30,480	25,098	0	142,675
K	480,390	475,501	2,925	3,487,891
PrIndex	0.681	0.174	0.329	1.053
NCFI	118,159	253,448	-112,409	1,998,014
DEP	33,582	49,319	0	326,959
ACRES	834	2,000	4	19,516
MTR	0.175	0.070	0.0000	0.356
ENTROPY	0.142	0.110	0.000	0.470

Table 52: Continued

OFFI	55,084	36,704	0	193,653
WC	222,504	760,816	-80,091	8,302,456
IR	0.070	0.009	0.052	0.087
Year= 2002				
I	30,726	39,758	0	279,322
K	414,726	290,198	23,228	1,347,893
PrIndex	0.640	0.159	0.359	1.043
NCFI	83,560	142,046	-60,315	698,117
DEP	31,904	40,696	0	241,316
ACRES	697	1,577	8	15,273
MTR	0.155	0.058	0.008	0.336
ENTROPY	0.133	0.096	0.000	0.401
OFFI	67,205	38,653	2,842	238,936
WC	76,204	137,800	-178,767	806,513
IR	0.060	0.006	0.047	0.076
Year= 2003				
I	31,139	38,718	0	230,984
K	421,001	339,627	24,559	2,165,338
PrIndex	0.695	0.144	0.409	1.058
NCFI	104,903	198,744	-85,983	1,540,516
DEP	28,090	36,702	0	192,349
ACRES	725	1,699	2	13,623
MTR	0.150	0.065	0.000	0.324
ENTROPY	0.131	0.099	0.000	0.438
OFFI	54,697	31,325	0	182,075
WC	113,884	176,274	-176,339	1,166,919
IR	0.059	0.006	0.042	0.075
Year= 2004				
I	41,904	73,438	0	684,521
K	500,252	691,849	67,100	7,374,659
PrIndex	0.764	0.144	0.453	1.068
NCFI	117,967	236,622	-81,656	1,842,675
DEP	31,356	44,205	0	267,537
ACRES	794	2,404	10	25,634
MTR	0.148	0.068	0.000	0.293
ENTROPY	0.130	0.101	0	0.465
OFFI	63,177	47,863	0	425,258
WC	151,867	319,472	-371,787	2,670,202
IR	0.062	0.006	0.051	0.075
Year= 2005				
I	32,080	39,669	0	209,408
K	468,270	461,596	10,030	3,695,406

Table 52: Continued

PrIndex	0.754	0.162	0.386	0.954
NCFI	121,281	216,874	-108,554	1,583,550
DEP	29,620	43,583	0	261,794
ACRES	703	1,289	5	9,187
MTR	0.164	0.064	0.000	0.309
ENTROPY	0.127	0.104	0.000	0.397
OFFI	58,979	38,813	0	302,759
WC	149,580	262,853	-11,052	1,983,501
IR	0.074	0.004	0.066	0.081
Year= 2006				
I	31,715	40,248	0	263,500
K	468,701	372,490	17,100	2,174282
PrIndex	0.750	0.166	0.411	0.992
NCFI	90,825	156,037	-118,027	674,389
DEP	28,984	40,074	0	282,651
ACRES	715	1,377	4	10,730
MTR	0.155	0.067	0.000	0.330
ENTROPY	0.132	0.096	0.000	0.369
OFFI	70,760	50,110	285	438,775
WC	167,350	255,348	-320,188	1,601,836
IR	0.086	0.003	0.074	0.092
Year= 2007				
I	37,172	56,716	0	424,010
K	503,528	452,133	30,525	3,125,297
PrIndex	0.856	0.126	0.602	1.010
NCFI	117,087	206,694	-166,336	1,154,692
DEP	30,745	40,437	0	238,176
ACRES	770	1,583	2	11,923
MTR	0.618	0.063	0.000	0.306
ENTROPY	0.135	0.097	0.000	0.381
OFFI	60,367	36,305	4,006	190,525
WC	148,418	204,523	-149,061	1,085,139
IR	0.088	0.005	0.081	0.104
Year= 2008				
I	33,884	42,832	0	197,880
K	486,702	542,734	26,750	5,015,650
PrIndex	0.876	0.113	0.525	1.010
NCFI	111,049	237,944	-257,996	1,887,667
DEP	40,456	92,545	0	918,054
ACRES	685	1,485	5	11,779
MTR	0.135	0.069	0.000	0.320
ENTROPY	0.134	0.104	0.000	0.441
OFFI	58,671	49,154	0	407,125

Table 52: Continued

WC	163,667	223,891	-33,260	1,289,742
IR	0.060	0.009	0.000	0.441
Year= 2009				
I	29,908	44,894	0	362,386
K	483,566	538,097	27,075	5,106,359
PrIndex	0.803	0.133	0.632	1.030
NCFI	145,582	492,127	-116,432	5,004,353
DEP	33,138	55,986	0	330,865
ACRES	664	1,393	9	10,994
MTR	0.134	0.068	0.000	0.350
ENTROPY	0.142	0.103	0.000	0.434
OFFI	59,367	41,259	3,126	353,524
WC	174,502	279,291	-81,738	1,967,753
IR	0.053	0.007	0.040	0.065
Year= 2010				
I	28,465	36,834	0	175,900
K	456,593	393,480	27,634	2,714,675
PrIndex	0.876	0.090	0.693	1.017
NCFI	109,984	193,612	-36,734	1,137,628
DEP	29,328	42,176	0	255,355
ACRES	615	1,269	3	9,615
MTR	0.149	0.065	0.000	0.330
ENTROPY	0.133	0.095	0.000	0.424
OFFI	62,643	46,185	333	376,591
WC	184,696	252,700	-12,048	1,783,301
IR	0.058	0.005	0.051	0.067
Year= 2011				
I	35,624	48,505	0	294,475
K	439,032	386,452	0	2,601,745
PrIndex	1.000	0.000	1.000	1.000
NCFI	113,441	196,777	-86,590	993,545
DEP	35,264	51,552	0	350,618
ACRES	579	1,145	2	9,554
MTR	0.148	0.066	0	0.350
ENTROPY	0.119	0.094	0.000	0.378
OFFI	60,350	36,108	6,202	237,286
WC	211,856	334,685	-153,105	2,285,123
IR	0.051	0.005	0.039	0.060
Year= 2012				
I	35,798	51,163	0	325,275
K	458,998	412,027	40,027	2,104,947
PrIndex	1.046	0.101	0.810	1.218

Table 52: Continued

NCFI	134,535	251,503	-264,414	1,347,264
DEP	31,602	41,535	0	187,986
ACRES	581	1,123	9	9,010
MTR	0.167	0.062	0	0.291
ENTROPY	0.131	0.099	0.00	0.433
OFFI	86,428	118,442	250	1,313,614
WC	215,849	368,422	-67,203	3,309,380
IR	0.048	0.004	0.037	0.056
Year= 2013				
I	38,084	57,886	0	348,309
K	476,117	472,145	43,367	2,698,808
PrIndex	1.090	0.098	0.864	1.230
NCFI	154,435	259,877	-74,251	1,243,048
DEP	37,408	62,693	0	496,960
ACRES	638	1,295	7	9,068
MTR	0.172	0.069	0.048	0.394
ENTROPY	0.116	0.092	0.000	0.360
OFFI	74,104	34,444	15,256	187,890
WC	212,473	519,872	-64,284	5,224,248
IR	0.046	0.007	0.036	0.062

SD= standard deviation, Min=minimum value, Max=maximum value
I= Investment= expenditures on buildings, equipment and machinery
K= Farm capital assets= total dollar value of assets including machinery, buildings, structures and equipment.
PrIndex=index of output prices. For more detail on its construction see data section and Table 11
NCFI=Net cash farm income is gross cash farm income (GCFI) less operating expenses. GCFI includes sales, changes in inventory, government payments to landlord, income from custom work and machine hire, income from royalties and leases for energy production, income from land rented to others, income from crops or livestock removed under production contract, changes in the value of inventories. This measurement does not include non-cash labor expenses or depreciation expenses.
DEP= tax depreciation expenses
MTR= federal marginal tax rate. Includes farm and off-farm income and adjustments for medicare and social security taxes on self-employment and social security income, deductions including social security taxes paid, domestic production activities credit and an adjustment for health care premiums paid.
ACRES= Physical farm size is measured as the total number of acres operated by the farm. This includes land rented from others and not including land rented to others.
ENTROPY= level of farm specialization. This variable ranks farms on a scale of 0-1, 0 being the most specialized and receiving 100% of yearly sales from a single crop/livestock product compared to 1 the least specialized with all crop/livestock products produced contributing equally to total farm sales.
OFFI= off-farm income. Includes earnings from wages, salaries and self-employment income as well as income from interest, dividends, and social security payments.
WC= Working Capital. Difference in farm current assets less short term debts.
IR= average across farm production regions of the interest rate on farm machinery loans. From the Agricultural Finance Databook.

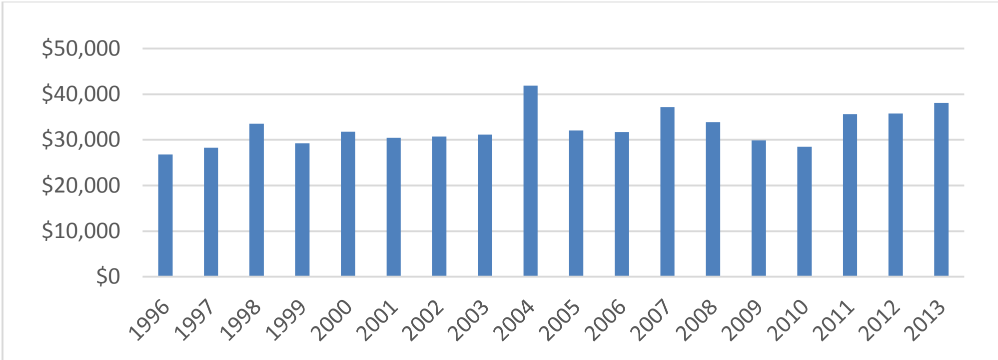

Figure 24: Mean of Investment (I) Annually for Pseudo Panel Dataset 1996-2013

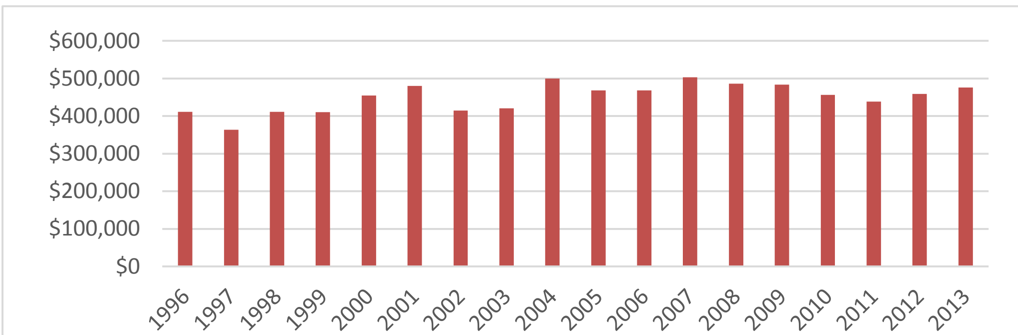

Figure 25: Mean of Capital Stock (K) Annually for Pseudo Panel Dataset 1996-2013

Figure 26: Mean of Output Prices (PrIndex) Annually for Pseudo Panel Dataset 1996-2013

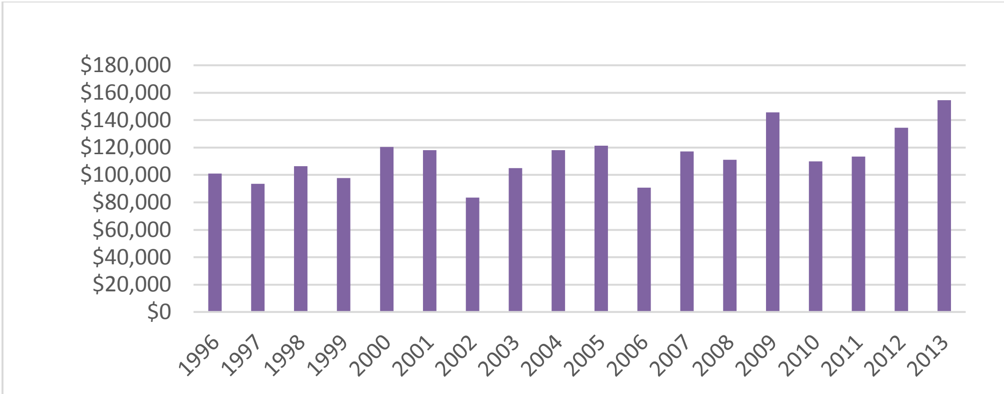

Figure 27: Mean of Net Cash Farm Income (NCFI) Annually for Pseudo Panel Dataset 1996-2013

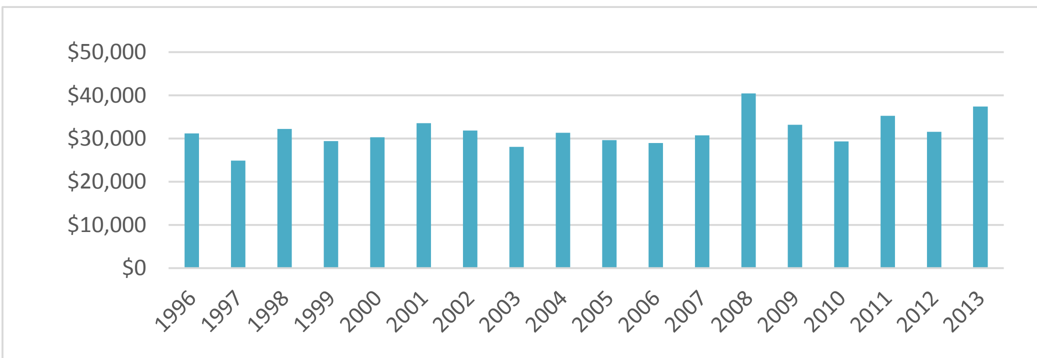

Figure 28: Mean of Tax Depreciation Expenses (DEP) Annually for Pseudo Panel Dataset 1996-2013

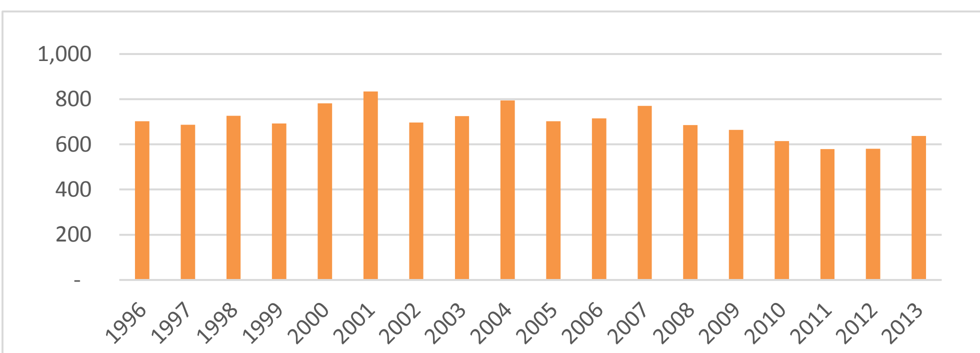

Figure 29: Mean of Acres operated (Acres) Annually for Pseudo Panel Dataset 1996-2013

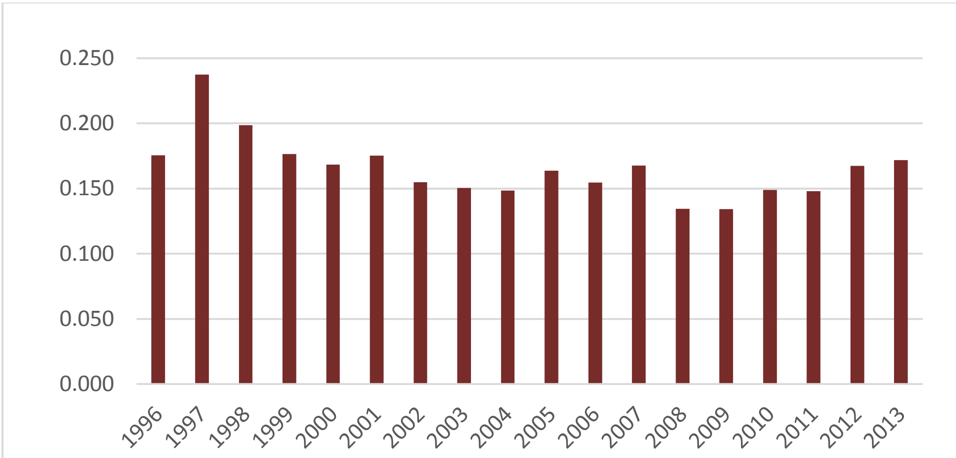

Figure 30: Mean of Marginal Tax Rate (MTR) Annually for Pseudo Panel Dataset 1996-2013

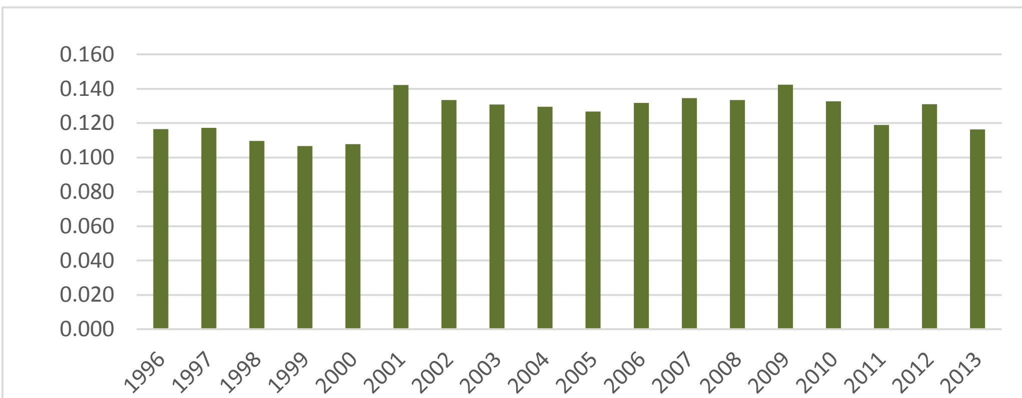

Figure 31: Mean of Farm Specialization (Entropy) Annually for Pseudo Panel Dataset 1996-2013

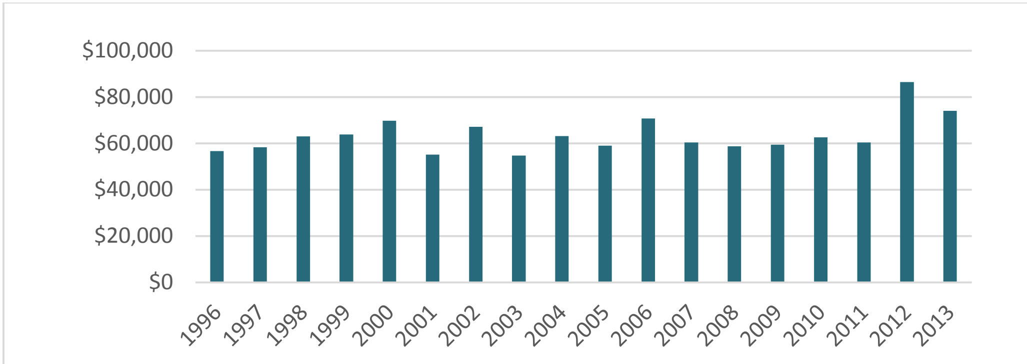

Figure 32: Mean of Off-farm Income (OFFI) Annually for Pseudo Panel Dataset 1996-2013

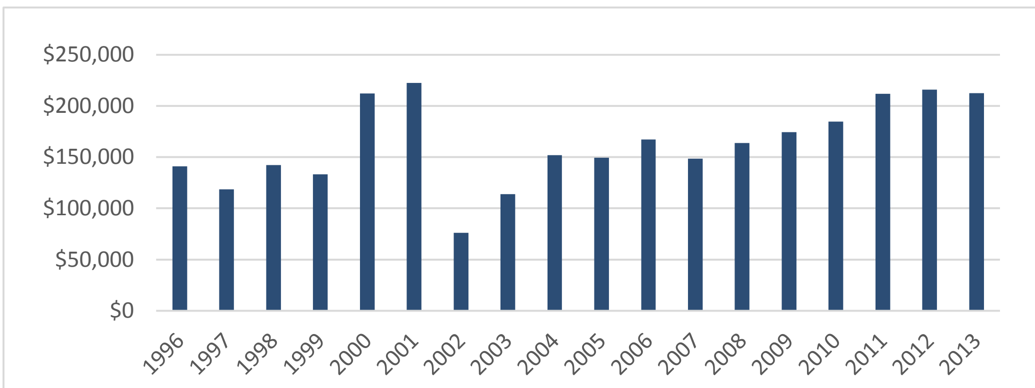

Figure 33: Mean of Working Capital (WC) Annually for Pseudo Panel Dataset 1996-2013

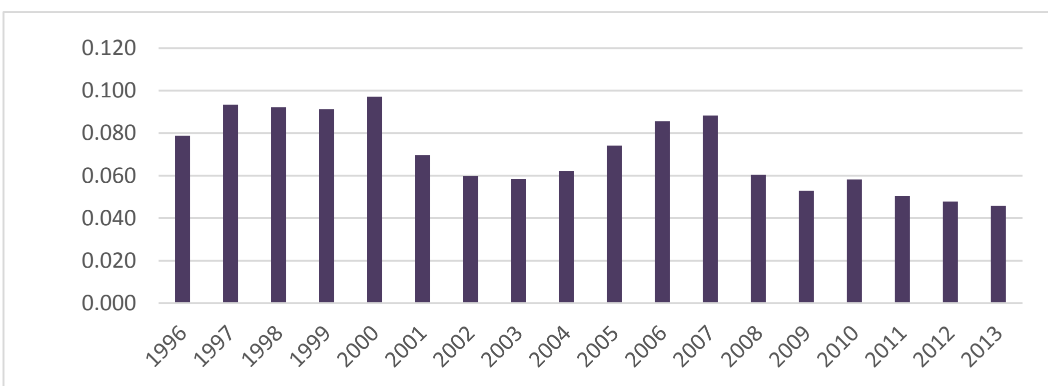

Figure 34: Mean of Interest Rates (IR) Annually for Pseudo Panel Dataset 1996-2013

VITA

VITA

EDUCATION

Purdue University. Ph.D. Agricultural Economics, Expected graduation May, 2016

University of California, Davis. M.S. in Agricultural & Resource Economics, 2003 with High Honors

University of California, Davis. B.S. in Managerial Economics, 2002 with Highest Honors

RESEARCH EXPERIENCE

Economic Research Service of USDA, *Intern*

May to August 2015

From FRED, BLS, and other sources gathered data to forecast US Farm National Assets and Debts Accounts; forecasted 2015 Farm Asset and Debt levels, researched forecasting methodology for VAR panel data models, summarized economic literature on the factors affecting farm debt and asset levels

August to December 2014

Reviewed literature on farm capital investment and tax policy; within STATA estimated the impact of tax policy on farm capital investment; developed a lengthy SAS program to calculate the marginal tax rate of farms using ARMS and IRS data

Purdue University Agricultural Economics Department, *Graduate Student Assistant,* 2012-present

Projects

- Optimal Replacement Policies for Biomass Rejuvenated Coal-Fired Electricity Plants, funded through the Office of Energy Policy and New Uses, USDA, current
- Farmland Values and Inflation, Department Project, 2012-2013
- Impact of Risk on Agricultural Production, funded through the Indiana Soybean Alliance Risk Initiative, 2012-2013

Teaching Assistant

- AGEC 250 “Agricultural Policy and Climate Change”, Spring 2014
- AGEC 217 “Macroeconomics”, Fall 2015
- Undergraduate seminar “The Business of Commercial Agriculture”, Spring 2013

Agricultural Issues Center, UC Davis, *Research Assistant,* 2002-2004

Designed surveys, trained survey administrators, used survey results to estimate impact of socioeconomic factors and grocery location on healthy food choice, reviewed literature on farm labor and pesticide usage

PROFESSIONAL EXPERIENCE

Guadalupe Associates, Inc., *Finance & Accounting Department,* 2008-2012

Performed inventory and sales database queries, used excel extensively for financial calculations and reports, resolve supplier and customer accounting issues

Law Offices of TCS, *Paralegal & Account Management,* 2006-2008

Legal research and document preparation, client management

Teaching:

Oak Grove High School, *Mathematics Student Teacher, 2005-2006*
Franklin McKinley School District, *K-12th grade Substitute Teacher, 2005-2006*
Sacramento Job Corps, *Mathematics GED Tutor/Instructor*, 2004-2005
Sylvan Learning Center, *Mathematics Tutor and Program Manager*, 2004-2005
DQ University, English Language Instructor, 2004-2005

JOURNAL ARTICLES

Williamson, James and Sarah Stutzman. "Tax Policy and Farm Capital Investment: Section 179 Expensing and Bonus Depreciation". *Agricultural Finance Review*. Status: accepted for publication.

Hubbs, Todd and Stutzman. "Corn Farm Liquidity and Short-Tem Asset Debt Choice." *Journal of Applied Farm Management*. Status: submitted for publication and awaiting response.

Yeager, Elizabeth and Sarah Stutzman. "Deer Creek Farms Case Study: Transitions into the Future". 2014. *American Journal of Agricultural Economics*. Vol 96 (2) pp 598-605.

PRESENTATIONS

Department Job Market Seminar. *Farm Capital Investment: Does Size Matter?* November 4, 2014

Stutzman, Sarah, "*Analyzing Farm Investment using ARMS survey data.*" Seminar for USDA ERS Staff, December 2014.

POSTERS

Stutzman, Sarah, "Small Farms and Investment", Indiana Small Farms Conference, Purdue Extension Service, 2016.

Stutzman, Sarah, “Who Invests in Capital: Propensity Score Analysis using ARMS Survey Data,” Department of Agricultural Economics, Purdue Snyder Lecture poster contest, Purdue University, 2015.

Stutzman, Sarah, “What’s For Dinner: Asymmetric Separability and Meat Demand.” 2014 AAEA Selected Presentation, St. Paul, MN., 2014

Stutzman, Sarah, “100 Years of Farmland Values and Inflation,” Department of Agricultural Economics, Purdue Snyder Lecture poster contest, Purdue University, 2013.

WORKSHOPS AND MEETINGS

Data

- Data Management, 16 Week Seminar, Purdue University, Spring 2016
- Agricultural Resource Management Survey Data, 2 day seminar, Economic Research Service USDA, 2015
- Big Data in Agriculture, Purdue University, 2014

Statistical Methodology

- Propensity Score Methods, Economic Research Service of USDA, 2014

Topic/Issues

- IFAMA Midwest Chapter Meeting, “Communicating with the public regarding large scale agriculture”, International Food and Agribusiness Management Association, 2014
- IFAMA Midwest Chapter Meeting, “Supporting the Growth of Agricultural Business in Africa” International Food and Agribusiness Management Association, 2013
- Strategic Risk Management, Purdue University Center for Food and Agricultural Business, 2012
- Research Issues: Research Integrity, Purdue University, 2012

Writing & Communicating

- Grant-Writing Strategies, Purdue University, 2012. Presenting Data using Graphics, Purdue University, 2015
- Writing Government Economic Reports, Economic Research Service of USDA, 2014
- Working with Print and TV Media: Communicating your Research Message, Purdue Graduate Student Seminar Series, 2016