FARM ADOPTION OF COMPUTER TECHNOLOGY

by

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LAND ACKNOWLEDGMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Overall computer ownership has been increasing among American farmers since 1997, however, it still remains well below US computer ownership as a whole. The general consensus is that more educated, younger farmers and those with bigger farms are more likely to adopt computers than other producers. Previous research has primarily focused on farm-level adoption in a specific state or region and thus have not looked at broader diffusion patterns. I use USDA and CPI data to model agricultural computer diffusion at the state level and analyze broader temporal and regional adoption trends. I use a two-way fixed effects model to look at overall diffusion trends, then decompose the effect of key variables in each year to compare across adoption groups. Similar to previous literature, I find that both farm size and share of dairy farms are positively associated with computer adoption, as well as internet access.

Chapter 1

OVERVIEW

1.1 Introduction

Overall computer ownership has been increasing among American farmers since 1997, however, it still remains well below US computer ownership as a whole (Census Bureau, 2016). Farms are fundamentally no different than any other business, producing a good or service while trying to minimize costs and maximize profits. Given the reliance of Americans on computers for work-related purposes, it is hard to imagine a business operating without a single computer, and yet a large proportion of farms do not own or lease even one.

There is relatively little existing research on computer adoption in agriculture (Shang et al., 2021; Gyawali et al., 2023; Drewry et al., 2019; Batte, 2005; Gloy and Akridge, 2000; Smith et al., 2004; Feder and Umali, 1993; Tiffin and Balcombe, 2011), and most consider the farm level and focus on a specific state or region (Tiffin and Balcombe, 2011; Batte, 2005; Smith et al., 2004; Gyawali et al., 2023; Drewry et al., 2019). These studies compare farmers across that region and have produced consistent and significant results, primarily, that age, education, and farm size are positively associated with computer adoption. I aim to build off of these farm-level adoption studies and look at broader state-level diffusion in the United States.

My main objective is to investigate whether significant farm-level attributes hold at the state level while controlling for regional and temporal variations. The central research question is: Which factors influence the speed and extent of the diffusion of computers in U.S. states? This research is considered hypothesis generating research, rather than hypothesis testing. It is intended to contribute to the existing literature and build a foundation for fu-

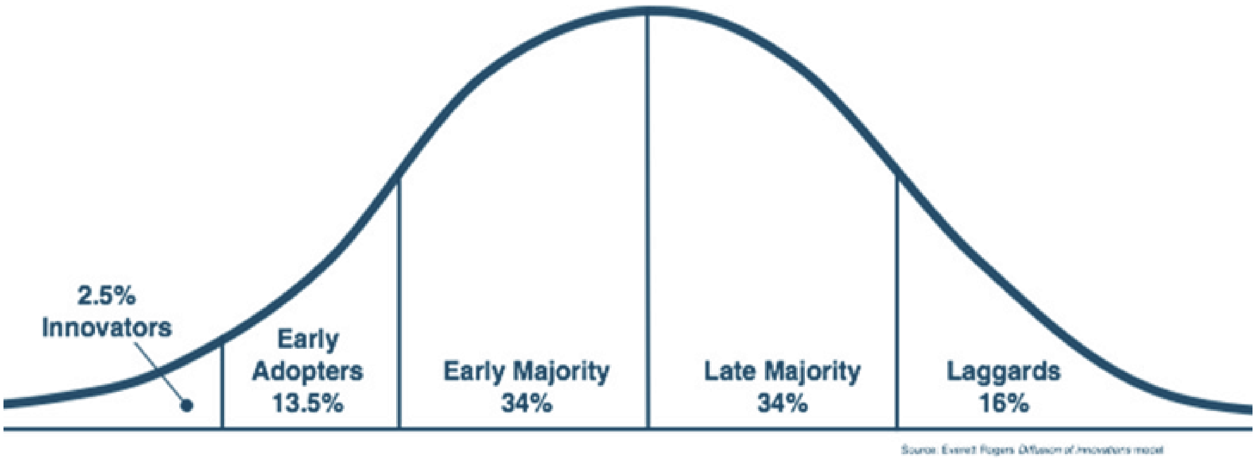


Figure 1.1: Roger's 5 Stages of Adoption (LaMorte)

ture research on the adoption of agricultural technologies but is not intended to make causal claims.

1.2 Literature Review

People who adopt a certain technology are typically grouped into 5 categories: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1958). The very first to adopt are the innovators, followed by the early adopters. These adopters are at the forefront of adopting the technology and informing others of their experiences. The early majority follows the initial set of adopters, and combined, these first three groups make up the first half of all adopters of the technology. At this point, the rate of adoption begins to decline, and the late majority comes into the picture. They adopt the technology near the tail end of the adoption process but are not the last to do so. The last group to adopt the technology are the laggards. By the time this group adopts the technology, everyone else who wants to already has. In the context of agriculture, the same groups exist. These groups are depicted in Figure 1.1.

The foundation of technology diffusion models is based on the logistic model, developed in the medical contagion literature. The idea is that the spread of technology adoption is similar to the spread of disease, with the disease, in this case, being information (Arrow, 1969). As the innovators and early adopters tell more people about the technology, more people adopt the technology and continue spreading the information they learn. The standard logistic

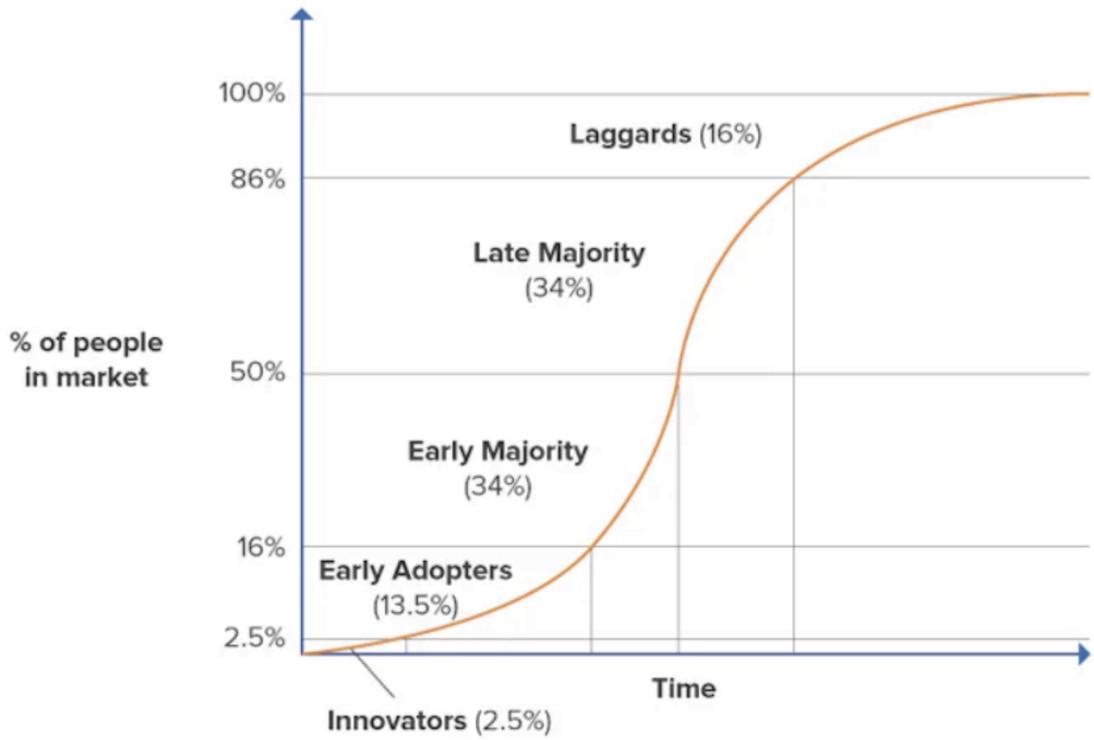


Figure 1.2: Cumulative S-Curve (Pro)

model assumes there is a homogeneous population and members have equal probability of receiving information about the technology from others (Feder and Umali, 1993). This is often referred to as the internal influence model, and looks like:

$$\frac{dC}{dt} = bC(t)(K - C(t)) \tag{1.1}$$

Where *C(t)* refers to cumulative adoption in time, t, K represents the adoption ceiling, and b is the coefficient of adoption.

There are a couple drawbacks to the standard logistic diffusion model, though. First, the model can only be used to explain adoption after some users have already adopted the technology (Geroski, 2000). It cannot explain why the innovators of technology adopt to begin with, it can only explain adoption from the information the innovators share with others. Furthermore, the logistic model produces a symmetric, S-shaped diffusion curve, depicted in Figure 1.2. However, symmetric adoption curves are rarely fit observed patterns in data (Feder and Umali, 1993; Geroski, 2000). In reality, the technology adoption path is long and bumpy and often, the later stages of adoption occur much more slowly than a typical S-curve may predict (Geroski, 2000).

Some studies have modified the standard logistic model to relax some assumptions or mitigate weaknesses. Other renditions of the logistic include flexible models, dynamic models, multi-innovation, and multi-stage diffusion models (Rao and Kishore, 2010). Bass (1969) is credited with the first multi-influence model, which accounts for the spread of internal and external information, attempting to explain how the first innovators of the technology adopt. This model is represented below:

$$\frac{dC}{dt} = [p + \frac{q}{K}(C(t))][K - C(t)] \tag{1.2}$$

Here, p represents the coefficient of innovation, q is the coefficient of imitation, and K is the adoption ceiling.

Many of these renditions have been used to estimate technology adoption in the agricultural sector. For example, Fernandez-Cornejo et al. (2002) use a dynamic diffusion model to look at the adoption of crop biotechnology. Drewry et al. (2019) analyze technology adoption among different producers in Wisconsin, looking at how adoption changes amongst producers of different commodities. Tiffin and Balcombe (2011) use a Bayesian approach to estimate both the adoption of organic farming practices and on-farm computer use. This is similar to the multi-innovation process Rao and Kishore (2010) outline in their review. Gyawali et al. (2023) use farm-level survey data to model the adoption of computer-based technologies (CBTs) in Kentucky. They used the standard logistic model to estimate CBT adoption. Smith et al. (2004) use survey data to look at adoption, usage, and perception of computer and internet adoption among Great Plains farmers. They also used the standard logit model to analyze adoption decisions.

In addition, the two-way fixed effects model is becoming the primary option for determining causality in panel data (Imai and Kim, 2021). It does have some drawbacks though. Imai and Kim (2021) argue that it is impossible to simultaneously control for unobserved unit and time-specific variables. Similarly, Kropko and Kubinec (2018) argue that while the results of the two-way fixed effect model are accurate, they are difficult to interpret and conceptualize and may not answer the broader research questions when applied to time series cross sectional data.

An alternative method to determining causality in panel data is to use the event study model. Comin et al. (2013) use an event study model, controlling for both location and time, to estimate the adoption level of technologies in different countries.

While all of these studies use differing approaches, they all model the adoption of a technology or practice. As it relates to this paper, there have been relatively few studies specifically on computer adoption in the agricultural sector, but several factors have emerged as significant determinants. Three factors have been consistently shown to affect farm computer adoption: education level, age, and farm size (Drewry et al., 2019; Gyawali et al., 2023; Tiffin and Balcombe, 2011). More educated, younger farmers are more likely to adopt, along with larger farms. Uniquely, Tiffin and Balcombe (2011) found a significant impact from farm commodity type. They show that dairy and organic farms are more likely to use computers than other commodity producers.

Alternatively, Drewry et al. (2019) found that gender plays an important role in internet use, using survey data to show that females are more likely to use the internet than their male counterparts. Interestingly, none of these studies find that farm income has a significant impact on computer adoption. Alternatively, Gloy and Akridge (2000) find that there is a positive relationship between farm income and the probability of adoption, but the marginal effect is so small that it is not economically meaningful. They also find that an increased number of employees on farms and increased use of written business plans have a positive effect on the probability of adoption.

Looking outside of the agricultural sector, Lin (1998) finds that higher income levels are associated with a higher likelihood of using a personal computer. She also finds age to be negatively associated with computer adoption, which is consistent with agricultural studies. Using country-level data, Caselli et al. (2001) find that the fraction of the labor force with better than primary education is associated with an increase in per-worker computer investment by the US.

Naturally, the biggest and most obvious questions surrounding computer use are what do farmers use computers for, and do they have an impact on productivity or profits? Batte (2005) finds that farmers get more utility from information processing applications than communication tools. In particular, the most utility comes from financial and production record-keeping tools (Batte, 2005). This suggests farmers use computers more for information management rather than looking at publications or reports from outside sources, or communication such as email and social media.

LoPiccalo (2022) studied the effect of improved internet connectivity on farm outcomes. She finds that faster internet speeds lead to higher corn and soybean yields, controlling for other factors. Also, higher internet penetration rates were shown to decrease farm expenses for farms with slower internet speeds. Similarly, Kandilov et al. (2017) show that two USDA broadband loan programs have positive impacts on farm sales, expenditures, and profits, but only in rural counties adjacent to metropolitan counties. Looking more broadly, Schimmelpfennig (2016) looks at precision agriculture technology and finds that there is a small but positive effect of adoption on farm profits.

Improved access to the internet has also been shown to boost rural economies. Whitacre et al. (2014) show that increases in rural broadband adoption are associated with increases in median household income and increases in the number of non-farm proprietors in rural areas. These effects are only seen with the adoption of technology, not with the mere availability of broadband. Similarly, Stenberg et al. (2009) find that higher adoption rates of broadband internet are associated with greater economic growth.

These studies provide a robust foundation for understanding the determinants of technology adoption and thinking about how agricultural computer adoption might be modeled.

Chapter 2

METHODOLOGY

2.1 Theory

The proportion of farms who own or lease computers in state, $\boldsymbol{i}$, and time, $\boldsymbol{t}$, considers multiple factors and can be expressed as a function, $\boldsymbol{f\ (I,\ T,\ R,\ S,\ P)}$. Here, the outcome is broken down into five key sets of variables: location, time, farm variables, producer variables, and price. $\boldsymbol{I}$ represents location, which could be state, region, division, etc. Location, $\boldsymbol{I}$, may inherently have a lower proportion of adopters, or the adoption rates of the area around it may influence how fast or slowly the technology is adopted. Variable $\boldsymbol{T}$ represents time.

Variables $\boldsymbol{R}$ and $\boldsymbol{S}$ represent sets of farm and producer specific variables which may affect adoption. $\boldsymbol{S}$ represents producer related factors such as gender, ethnicity, and age. $\boldsymbol{R}$ represents farm specific factors, such as lot size, household size, and commodities being produced. $\boldsymbol{P}$ simply represents the price of computers, which is the basis of any demand function.

2.2 Two-Way Fixed Effects

I compare two different empirical methods of estimating computer adoption rates. First, a two-way fixed effects model is used to estimate effects on the proportion of farms that own or lease computers. While it has some weaknesses, as previously mentioned, these are largely mitigated since results are not being used to make causal inferences. This model assumes the effect of each variable is constant across time, while controlling for time and state level unobservables. The model is as follows:

$$Y_{it} = \alpha + i_i + t_t + \beta_1 \text{Dairy}_{it} + \beta_2 \text{Age}_{it} + \beta_3 \text{Gender}_{it} + \beta_4 \text{Size}_{it} + \beta_5 \text{Income}_{it} + \beta_7 \text{Internet}_{it} + \beta_6 \text{P}_{it} + \lambda \text{R}_{it} + \varepsilon_{it} \tag{2.1}$$

where:

Dairy: Proportion of total operations that are dairy producers by state

Age: Average age of day to day decision-maker

Gender: Proportion of female day to day decision-makers

Size: Total acres per operation in each state

Income**:** Farm-related income per operation in each state

Internet: Proportion of farms with internet access

P**:** Price for computers measured in CPI (region-specific)

R: Other controls (see table 3.2)

Note: all for state, i, and year, t

The left-hand side variable, Y_{it}, represents the proportion of farms that own or lease computers in state, i, in year, t. Location and time are the two fixed effects I am controlling for on the right-hand side, represented by i_i for state and t_t for year, respectively.

The variables included in the control group are not significant in previous studies but seem important to control for. However, there are several key variables I do expect to be significant determinants of the dependent variable. Tiffin and Balcombe (2011) suggest that dairy farms are more likely to adopt computers than other commodity producers. They suggest it could be due to the fact that farms where dairy comprises two-thirds or more of total production are more likely to use precision agriculture equipment and robotic milking technology. Therefore, I'd expect a significant, positive coefficient to be associated with the proportion of dairy farms in each state. Age is significant at the farm and household level consistently (Drewry et al., 2019; Lin, 1998; Tiffin and Balcombe, 2011), and I would expect that to continue at the state level as well. More specifically, I'd expect a significant and negative coefficient.

Furthermore, I expect that states with higher proportions of female farmers will have higher proportions of farms that own or lease computers (Drewry et al., 2019). Similarly, I expect states with larger acres per operation to be more likely to adopt. This follows previous studies which have shown that larger farms are more likely to own or lease computers than smaller farms (Drewry et al., 2019; Gloy and Akridge, 2000).

I also expect a positive relationship between income and the proportion of farms that own or lease computers. This has been outlined in previous studies (Gloy and Akridge, 2000; Lin, 1998) and follows the law of demand.

2.3 Coefficient Decomposition

Alternatively, the event study model interacts time with other key variables allowing the effects of each variable to change over time. This is a key difference from the previous model and presents the opportunity to look deeper at the effect of each variable. The event study model looks like:

$$Y_{it} = \alpha + i_i + t_t + \beta x_{it} T_t + \lambda R_{it} + \varepsilon_{it} \tag{2.2}$$

Here, the $\beta x_{it} T$ term is the interaction between the choice variable and year T, i_i represents state fixed effects, and t_t represents year fixed effects. For each variable, there will be a unique coefficient for each year.

The λR term represents the controls. These coefficients are estimated but are not interacted with time, so each of these variables only has one coefficient.

Typically, event study models are used to assess the effect of a treatment, comparing a before and after period for a treated and untreated group. In event studies, the treatment is dynamic, so the model can be better thought of as a heterogeneous effects model, where the effects of the choice variables vary across time.

Several categorical variables required base groups to be defined. For ethnicity, I used the proportion of white-run farms as the base, providing the opportunity to look at the effect of increased or decreased diversity across states and time. For time, 2001 was chosen as the base year. The US average adoption of computers was closest to 50% in that period, so that allows me to compare early adopters to later adopters, which is particularly useful with the event study model.

Chapter 3

DATA

Most data comes from the USDA National Agricultural Statistics Service (NASS), more specifically, the Census of Agriculture. Data for the variables *own or lease computers* and *internet access* come from the June Agricultural Survey. Questions about these variables were asked in odd-numbered years from 1997 to 2023. Other data for explanatory variables comes from the USDA Agricultural Census, for which data is available from 1997 to 2022 in 5-year increments.

The variables *own or lease computers* and *internet access* are measured as a percentage, share of farms in each state. In earlier years, states with low response rates were aggregated in the June Agricultural Survey but may show up individually later on. This creates an unbalanced panel dataset. In years where states are aggregated, data for independent variables is matched to the parent state. For instance, if multiple states are grouped into Colorado, I would match that dependent variable to independent variables associated with Colorado, ignoring the data for the other states in that group. Data from the Agricultural Census is available for all states, though there may be different patterns of missing values across states.

Since the data from the Census of Agriculture occurs every five years compared to every other year in the June Agricultural Survey, the data do not match up perfectly. Years where data matched were left alone. For years where the data did not line up, imputation techniques were used. For data from the June Agricultural Survey, which only occurs in odd-numbered years, the average of the two neighboring odd-numbered years were averaged to estimate the value of the even-numbered years. For example, the value of 2012 would be the average of the 2011 and 2013 values.

For the USDA Census data, the missing values were imputed using a different, data driven approach. The data were broken up by state, I then individually regressed the variables with missing values on time to get a unique estimated coefficient for each variable. I then used that coefficient to estimate the missing values for each variable. For example, to fill in the missing values for the number of dairy farms in each state, the observed number of dairy farms was regressed on year. This produces a coefficient representing how dairy farms change across time. This coefficient is then used to estimate values for all time periods in the dataset, which were used to fill in missing values in the data. Since almost all of the variables with missing values were count variables, any values that were imputed with values less than 0, were coded to 0. In addition, new proportion variables were created to use in the models which are more comparable across states. However, there were extraneous values imputed for 2023, which did not seem to fit with the overall pattern of the observed data, so 2023 is dropped for modelling purposes. So, while the data collected with the dependent variable is available in 2023, the complete dataset only extends to 2022, which is the last observed year of the USDA Census of Agriculture data.

CPI data on computers was collected from the Federal Reserve. The CPI data is available for every month from December 1997 to December 2023. In addition, I collected regional CPI data from the Bureau of Labor Statistics for each of the four census regions. I used the values for the month of June, to match the time when the June Ag. Survey questions are being asked. To get variation in CPI across states, I used the regional CPI to create a new, regionally adjusted measure for the CPI of computers. This produces a different value for the price of computers in each census region. This CPI data will be used to account for the price of computers changing over time and to account for differences across states. Regional CPI values were re-based on December 2007, to match the base year of the computer CPI data.

Table 3.2 contains each of the explanatory variables I have data for, the source, and my expectation of their impact on the dependent variable based on previous studies. To get a better idea of how these variables are changing over time I look at the coefficients of variation for each of my variables of interest. These are presented in Table 3.1.

Table 3.1: Key Explanatory Variables Coefficients of Variation

Variable	**C.V.**
% of Dairy Operations	1.45
Average Age	0.04
% of Female Decision-makers	0.52
Acres per Operation	1.09
Income per Operation	0.62
% with Internet Access	0.33
Computer CPI	1.57

There are some interesting trends to note in the raw data. Looking at Figure 3.1, there appears to be an upward trend in adoption percentage for all four Census regions. The South remains below while the other regions are converging. One reason for this difference could be related to income. The South has a lower median household income (USD), so the price burden may be higher there than other regions.

The next logical question becomes whether computer adoption is actually changing. The dependent variable, *% Own or Lease Computers*, can be expressed as a proportion:

$$\text{\% Own or Lease} = \frac{\text{Total \# of Farms that Own or Lease}}{\text{Total \# of Farms}} \tag{3.1}$$

Theoretically, the upward trend observed in the raw data *could* be driven solely by a decrease in the denominator, and not have anything to do with computer ownership. If this was the case, any observed results would be reflective of the total number of operations in each state, rather than computer adoption.

With data on the total number of operations in each state, I can rearrange 3.1 to get:

$$\text{\% Own or Lease} \times \text{Total \# of Farms} = \text{Total \# of Farms that Own or Lease} \tag{3.2}$$

A t-test between 1997 and 2022, shows a statistically significant difference between the two time periods with $p = 0.018.$, rejecting the hypothesis that there is no difference between the two time periods. This provides reassurance that there is actual change occurring with

Table 3.2: Key Explanatory Variables and Expectations

Variable	**Data Source**	**Expectation**	**Previous Studies**
% of Dairy Operations	U.S. Department of Agriculture (b)	Positive	(Tiffin and Balcombe, 2011)
Average Age	U.S. Department of Agriculture (b)	Negative	(Drewry et al., 2019; Tiffin and Balcombe, 2011; Lin, 1998)
Ethnicity	U.S. Department of Agriculture (b)	Control	
% of Female Decision-makers	U.S. Department of Agriculture (b)	Positive	(Drewry et al., 2019)
Acres per Operation	U.S. Department of Agriculture (b)	Positive	(Drewry et al., 2019; Gloy and Akridge, 2000)
% of Crop Operations	U.S. Department of Agriculture (b)	Control	
% of Poultry Operations	U.S. Department of Agriculture (b)	Control	
Income per Operation	U.S. Department of Agriculture (b)	Positive	(Gloy and Akridge, 2000; Lin, 1998)
% with Internet Access	U.S. Department of Agriculture (a)	Control	
Avg. Household Size	U.S. Department of Agriculture (b)	Control	
Computer CPI	St. Louis Federal Reserve	Negative	
Regional CPI	U.S. Bureau of Labor Statistics (2023)	Control	
% Off-Farm as Primary Employment	U.S. Department of Agriculture (b)	Control	

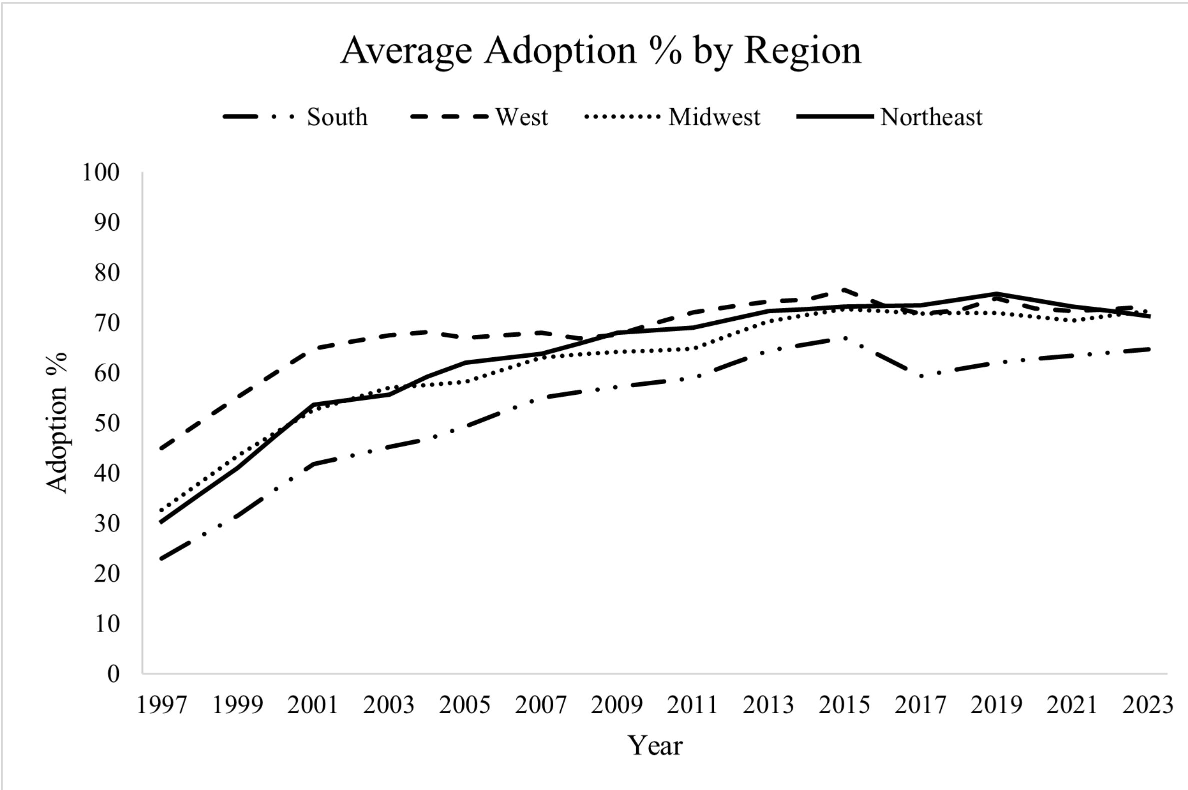


Figure 3.1: Average Adoption % by Region

computer adoption, indicating the change in the overall proportion is not being driven solely by a decrease in the number of operations.

A similar trend can be seen looking at Figure 3.2 , with internet access across time. Again, the South begins below but all regions converge, and by 2023, they are all at the same level, right around 80%.

An interesting observation to note between the two charts is that at the beginning of the observed time period, a higher proportion own or lease computers than have internet. This implies that there is at least some subset of the population who are purchasing computers, knowing they do not have internet access. This could be indicative of previous literature, suggesting farmers use computers for information management purposes, which does not inherently require internet access.

Looking at price changes over time can also provide valuable insight into why adoption is increasing. Looking at the consumer-side CPI for computers in Figure 3.3, there is a sharp decrease in price from 1997 to 2003. Price then levels out and remains relatively constant for

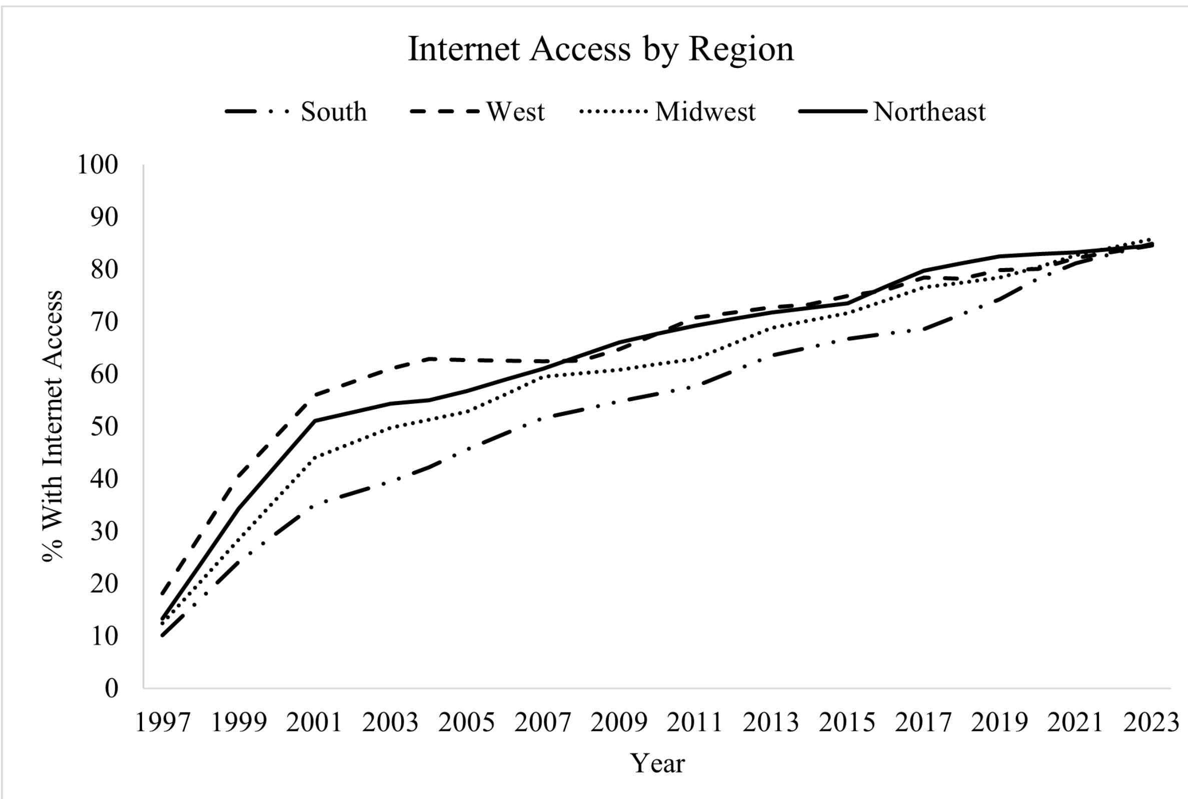


Figure 3.2: Internet Access By Region

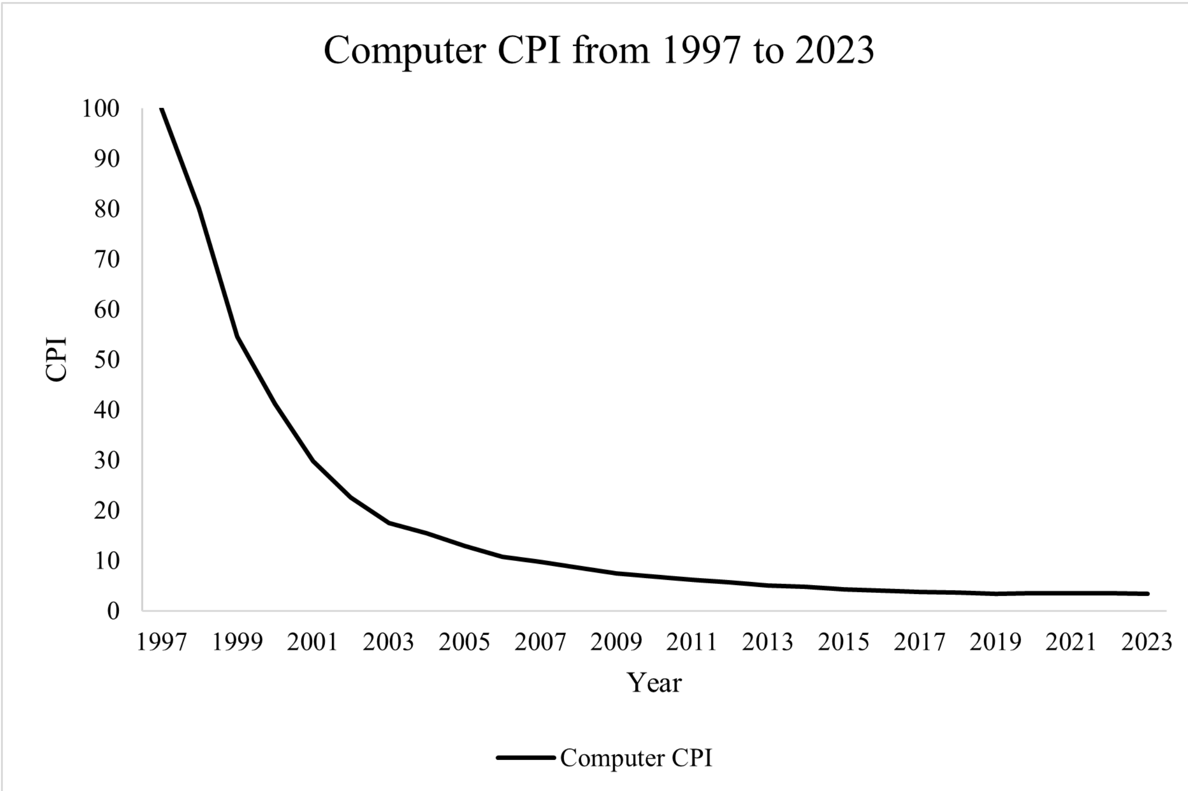


Figure 3.3: Price of Computers Over Time

the back half of the observed time period. This is likely due to a combination of production costs going down resulting in mass production, driven by technological advancements. These observed patterns in the raw data can be used to hypothesize what results might look like.

Chapter 4

RESULTS

I look at three different models, building up to the full two-way fixed effects (TWFE) model. Starting with a basic OLS model with no fixed effects, looking at each fixed effect (state and year) individually, and then both together in the final TWFE model. Lastly, results from the event study are looked at and the two models are compared.

4.1 Two-Way Fixed Effects Results

Results for the TWFE model and the three models building up to it are shown in Table 4.1 below. As mentioned previously, the data used for this model omits the year 2023. These models control for all of the variables mentioned in Table 3.2, though none of those controls are reported with the exception of internet access. The dependent variable for these models is the % of farms who own or lease computers.

Starting with Model 1, the most obvious issue is the positive coefficient associated with CPI, the proxy for price. This contradicts conventional economic theory, and suggests a basic OLS model with no fixed effects may not be the best model to use. Looking at models 2 and 3 which have state and year fixed effects respectively, only internet access appears to be significant in both models. The positive coefficient on income in model (3) fits with conventional wisdom as well, though does not appear to be economically meaningful. The final two-way fixed effects model (4) fits much more closely with the state fixed effects model (2) than the others. The 3 significant variables, *% dairy farms*, *acres/operation*, and *internet access* have coefficients that fit with what previous literature has suggested.

Coefficients should be interpreted as a 1-unit change in variable x is associated with a β percentage point change in the proportion of farmers who own or lease computers. For

Table 4.1: TWFE Results

VARIABLES	(1)	(2)	(3)	(4)
% Dairy Farms	5.866	**8.815****	-0.558	**11.54*****
	(3.744)	(3.952)	(2.763)	(3.990)
Acres/Operation	6.80e-06	**6.25e-05***	1.01e-05	**6.36e-05***
	(8.77e-06)	(3.45e-05)	(7.39e-06)	(3.51e-05)
% Female	**-0.380*****	**-0.380*****	-0.0211	-0.218
	(0.0684)	(0.0764)	(0.0987)	(0.198)
% Internet Access	**0.864*****	**0.653*****	**0.929*****	**0.650*****
	(0.0494)	(0.0559)	(0.0460)	(0.0619)
Income ($1,000/Op.)	**8.29e-05***	8.05e-05	**8.95e-05***	5.93e-05
	(4.60e-05)	(5.15e-05)	(4.77e-05)	(6.28e-05)
Adj. CPI	**0.00563*****	0.000852	0.0187	-0.0113
	(0.00197)	(0.00183)	(0.0423)	(0.0447)
Avg. Age	-0.203	**1.033*****	-0.300	0.505
	(0.316)	(0.335)	(0.375)	(0.624)
State FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
# of Obs.	994	994	994	994
R-Squared	0.921	0.953	0.937	0.957
F-stat	**11.77*****	**3.72*****	**10.81*****	n/a

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

example, the *% of dairy farms* has a coefficient of 11.54, meaning that a 1 percentage point increase in the share of dairy farms is associated with a 11.54 percentage point increase in the share of all farms that own or lease computers.

This is a very large and statistically significant coefficient at the 1% level of confidence. There are a few reasons why this could be the case. Drewry et al. (2019) find that approximately 3% of surveyed Wisconsin farmers use robotic dairy milking machines. Furthermore, they find that farms whose output is at least two-thirds dairy are significantly more likely to use precision planting equipment. Additionally, MacDonald et al. (2020) show that over time, dairy farms are consolidating, meaning the average size of dairy farms is increasing.

These findings suggest two logical reasons why dairy farms would contribute so much to overall adoption. First, adopting any agricultural technology, such as robotic milking or precision planting machinery, could suggest an inherent willingness to adopt any agricultural technology, computers or otherwise. Similarly, these technologies are typically computer dependent, so adopting either of these technologies may require computer adoption by farms who otherwise would not adopt. Alternatively, results from the TWFE model also show a positive and statistically significant coefficient associated with farm size. If dairy farm size is increasing across time, then the positive coefficient observed with farm size could also have an influence. In this case, the inherent technology use associated with dairy farms coupled with the fact that dairy farms are getting larger would be contributing to the large observed coefficient.

Internet access is highly statistically significant and positive. This makes intuitive sense, as improved internet access improves the usefulness of computers, which would increase the number of people who would use them. However, based on previous literature suggesting that farmers use computers for mostly non-internet uses, I would not expect that this would be a significant determining factor of adoption. The relatively small coefficient seems to fit with that theory.

Reported F-statistics compare each of the first 3 restricted models to the final TWFE (4) model. While all three restricted models are statistically different than the full model, the state fixed effects model (3) seems to be much closer to the full TWFE model. This suggests that in the final model, the year fixed effects do not have as strong of an effect. This could be due to the fact that internet access is highly correlated with time, so it is likely picking up much of that effect already.

Interested readers may view the TWFE results for the non-imputed dataset in Table A.1. The large decline in observations illustrates the trade off between imputation and loss of precision in estimation.

4.2 Decomposition Results

The results from the event study model show how each estimated coefficient changes across time. While the TWFE regression gives a good idea of what is generally significant, the event study provides insight into which periods certain variables were significant. Recall, 2001 is used as the base year, so coefficients from this model can be used to compare early adopters to later adopters. Table 4.2 illustrates the results from the event study model.

Table 4.2: Event Study Results

Year	(1) Dairy	(2) Acres/Op.	(3) Female	(4) Internet	(5) Income	(6) Price	(7) Age
1997	16.70	**2.30e-05***	0.482	**0.841*** **	**0.809*** **	**0.185** **	-0.355
	(13.19)	(1.21e-05)	(0.299)	(0.192)	(0.257)	(0.0854)	(0.522)
1998	8.855	1.64e-05	0.229	**0.446*** **	**0.438*** **	0.130	-0.417
	(11.08)	(1.17e-05)	(0.200)	(0.0877)	(0.129)	(0.0796)	(0.423)
1999	0.231	1.13e-05	-0.0399	0.0938	0.183	0.0136	-0.529
	(9.771)	(1.45e-05)	(0.139)	(0.0842)	(0.111)	(0.0834)	(0.421)
2000	0.478	5.47e-06	-0.00566	**0.0771***	**0.116***	0.0346	-0.282
	(5.274)	(7.18e-06)	(0.0826)	(0.0405)	(0.0589)	(0.0613)	(0.215)
2002	-0.0845	-6.09e-06	0.105	3.84e-06	-0.0299	-0.0346	0.356
	(3.543)	(6.89e-06)	(0.152)	(0.0400)	(0.0983)	(0.0593)	(0.342)
2003	-1.941	-7.64e-06	0.121	-1.10e-05	-0.00362	-0.154	0.463
	(5.305)	(1.00e-05)	(0.196)	(0.0668)	(0.110)	(0.145)	(0.522)
2004	5.253	-1.21e-05	0.313	0.0330	-0.0332	-0.120	0.260
	(6.778)	(1.08e-05)	(0.225)	(0.0635)	(0.122)	(0.183)	(0.476)
2005	14.37	**-3.74e-05** **	0.468	-0.0115	-0.0310	-0.150	0.327
	(10.30)	(1.81e-05)	(0.283)	(0.0926)	(0.171)	(0.329)	(0.575)
2006	5.650	**-3.29e-05** **	0.436	-0.0313	-0.0226	**-1.542***	0.453
	(8.412)	(1.61e-05)	(0.265)	(0.0899)	(0.146)	(0.890)	(0.585)

Continued on next page

Table 4.2 – Continued from previous page

Year	(1) Dairy	(2) Acres/Op.	(3) Female	(4) Internet	(5) Income	(6) Price	(7) Age
2007	-3.310	-1.56e-05	**0.437***	-0.0546	-0.00961	1.751	0.771
	(7.531)	(1.34e-05)	(0.247)	(0.110)	(0.146)	(1.846)	(0.668)
2008	2.650	**-2.30e-05***	0.369	-0.0425	-0.0613	**-3.463***	0.544
	(6.707)	(1.34e-05)	(0.247)	(0.104)	(0.144)	(2.024)	(0.589)
2009	7.828	**-2.75e-05****	0.274	-0.0172	-0.109	**-7.268*****	0.287
	(6.657)	(1.29e-05)	(0.253)	(0.0929)	(0.152)	(2.526)	(0.582)
2010	6.008	**-2.38e-05***	0.304	-0.0489	-0.114	-1.747	0.514
	(6.613)	(1.20e-05)	(0.253)	(0.0944)	(0.159)	(1.065)	(0.571)
2011	5.765	**-2.03e-05***	0.368	-0.0403	-0.117	-1.000	0.801
	(6.897)	(1.16e-05)	(0.254)	(0.0984)	(0.170)	(0.979)	(0.588)
2012	4.909	-1.27e-05	0.402	-0.109	-0.165	-2.173	0.932
	(6.948)	(1.17e-05)	(0.251)	(0.114)	(0.198)	(1.673)	(0.557)
2013	4.924	-1.41e-05	0.391	-0.169	-0.171	-1.780	**0.983***
	(7.262)	(1.20e-05)	(0.269)	(0.123)	(0.205)	(1.662)	(0.553)
2014	4.014	-9.34e-06	0.362	-0.205	-0.159	-3.614	**1.021***
	(7.157)	(1.17e-05)	(0.277)	(0.127)	(0.201)	(2.197)	(0.515)
2015	2.640	-2.06e-06	0.345	-0.197	-0.154	-3.664	**1.000****
	(7.158)	(1.11e-05)	(0.287)	(0.142)	(0.199)	(2.219)	(0.492)
2016	7.716	-1.35e-05	0.317	-0.0391	-0.0432	2.395	0.267
	(6.924)	(1.05e-05)	(0.288)	(0.114)	(0.202)	(2.193)	(0.574)
2017	12.55	-1.95e-05	0.316	0.0654	0.0202	2.530	-0.550
	(8.310)	(1.40e-05)	(0.316)	(0.120)	(0.217)	(1.635)	(0.862)
2018	13.24	-2.26e-05	0.337	0.0586	0.0112	1.136	-0.352
	(8.122)	(1.55e-05)	(0.294)	(0.110)	(0.219)	(1.300)	(0.800)
2019	12.81	-9.67e-06	0.343	0.0344	0.0200	-0.190	-0.322
	(8.481)	(1.49e-05)	(0.297)	(0.104)	(0.225)	(1.027)	(0.846)
2020	**18.68****	-1.65e-05	0.423	0.0725	0.0608	0.367	0.365
	(7.906)	(1.74e-05)	(0.299)	(0.103)	(0.234)	(0.928)	(0.880)
2021	**20.93****	-1.93e-05	0.504	0.131	0.0811	0.705	1.075
	(9.709)	(2.08e-05)	(0.303)	(0.111)	(0.242)	(1.296)	(1.012)
2022	15.75	-2.79e-05	0.385	0.123	0.0232	1.167	0.675
	(10.02)	(2.14e-05)	(0.265)	(0.107)	(0.236)	(1.156)	(0.920)
n	994	994	994	994	994	994	994
R^2	0.958	0.959	0.958	0.962	0.960	0.959	0.959
Contr.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

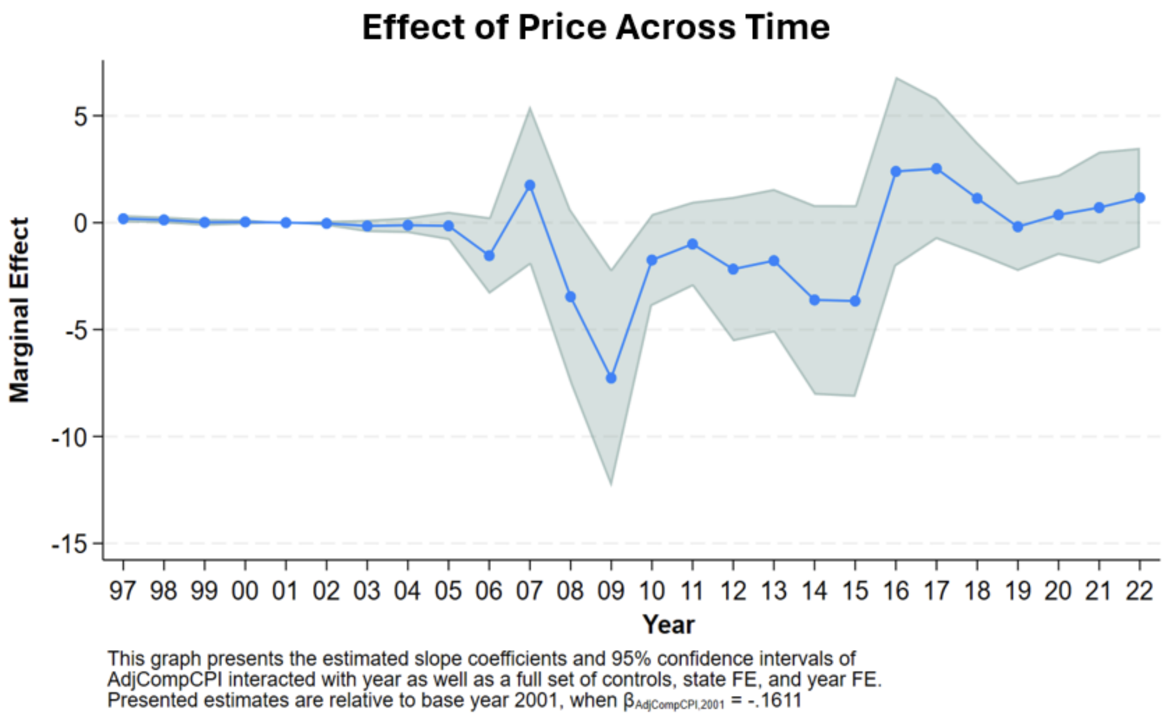


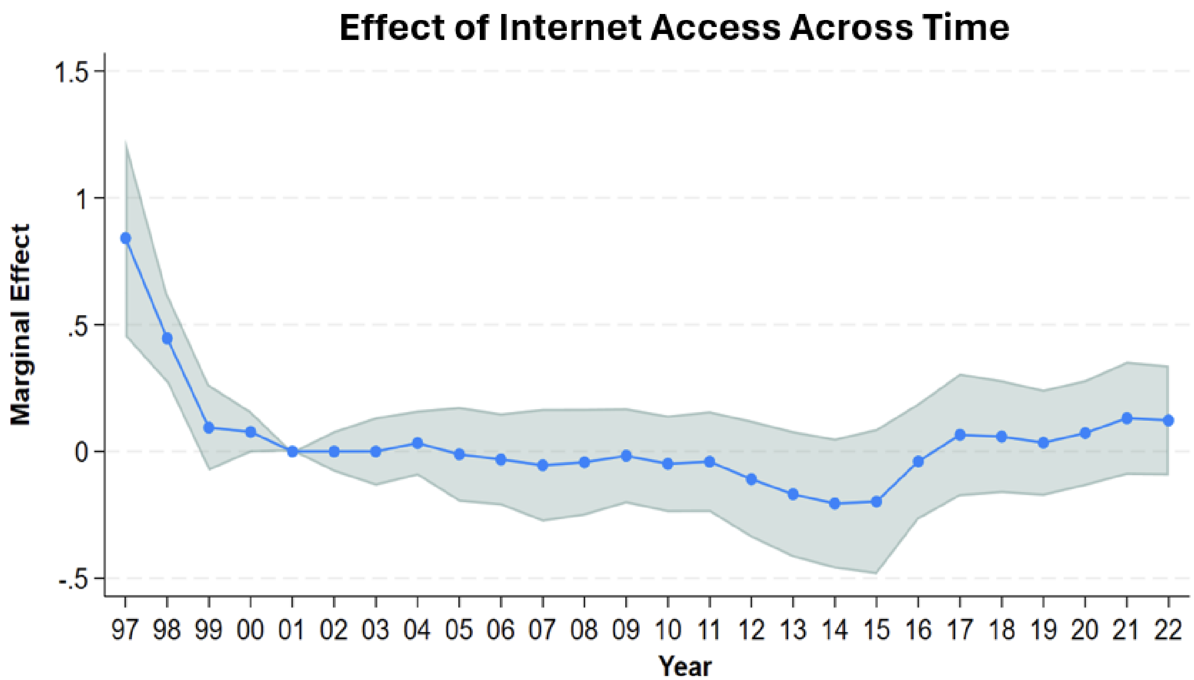
Figure 4.1: Price Coefficient Across Time

Coefficients from this model represent relative to average change by year, compared to the relative to average change in 2001. Coefficients should be interpreted as follows: on average, a one unit increase in variable x in year t, will increase computer ownership by β percentage points more than existed in that location in 2001, in addition to the what would otherwise occur with the year to year spread of the technology.

The positive coefficient associated with *price* (6) in 1997, for example, does not mean that price had a positive effect on computer ownership. Rather, it suggests that the effect of price was stronger in 1997 than in 2001. Looking back to Table 3.3, this makes sense, as most of the change in price occurs early on. Table 4.1 depicts the effect of *price* (6) over time.

Looking at these results, it appears that *internet access* (4) is consistently statistically significant and positive early on, but loses its significance later. This effect is depicted in Figure 4.2.

Age (7) is not significant early on, but appears to be mildly significant later (Figure 4.3). The positive coefficient suggests age played more of a role later in the adoption stage than



This graph presents the estimated slope coefficients and 95% confidence intervals of InternetAccess interacted with year as well as a full set of controls, state FE, and year FE. Presented estimates are relative to base year 2001, when $\beta_{InternetAccess,2001} = .6093$

Figure 4.2: Internet Access Coefficient Across Time

early on. Similarly, it appears that while *% dairy operations* (1) is not significant early on, it becomes significant in 2020 and 2021, at the 5% level of significance. This could represent changes in the nature of the dairy industry such as consolidation, as mentioned previously. Similarly, it may be a reflection of a growing opportunity cost of not using computers. This effect is depicted in Figure 4.4.

Alternatively, *acres* (2) appears to be significant for the first half of the time period, but is not later. The positive coefficient in 1997 suggests it was more of a determining factor for those early adopters. Alternatively, the negative coefficient observed later on suggests as adoption moved further along, farm size became less of a factor. Similarly, *income* (5) is statistically significant three of the first four years and then not again. Early on, the significance is likely driven by the relative expense of computers compared to the money farms were actually earning. As farms made more money, they were able to overcome that threshold. As prices fell, this became less of a hurdle and computers became more affordable for more farms, regardless of income.

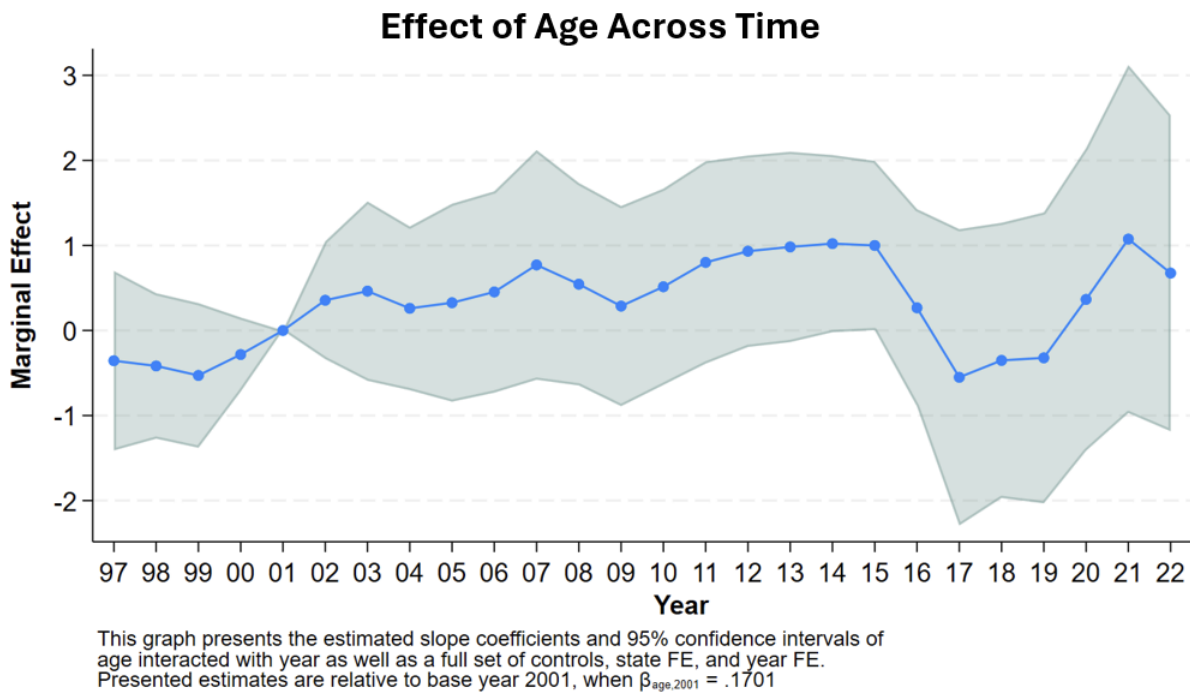


Figure 4.3: Age Coefficient Across Time

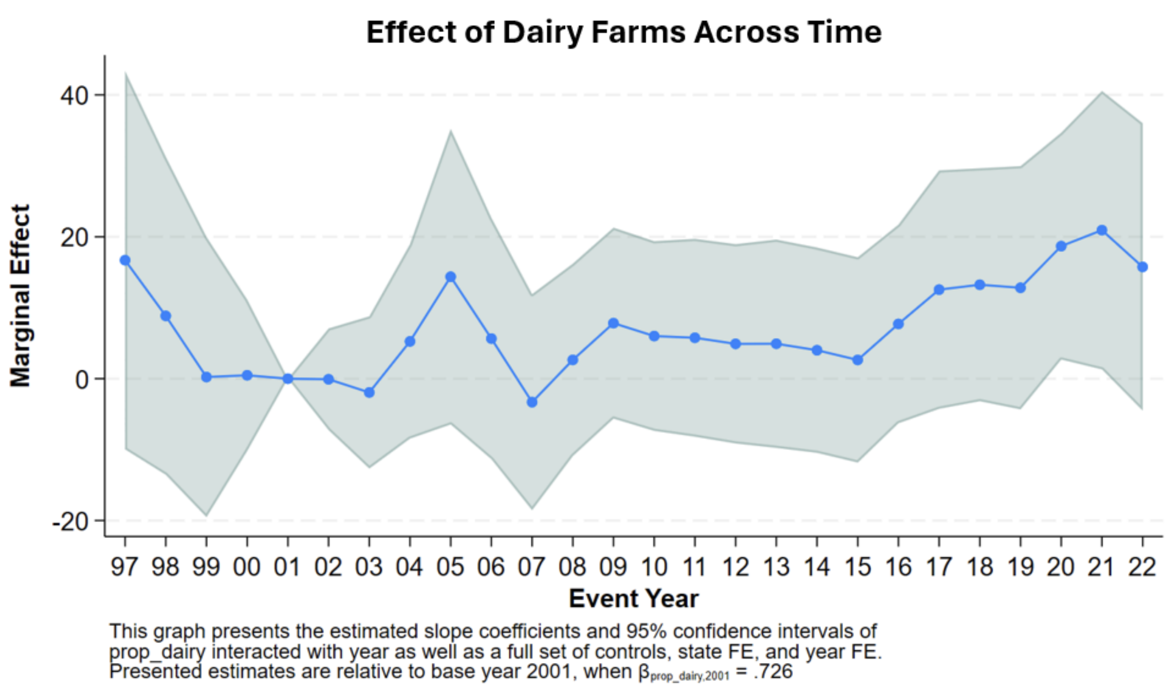


Figure 4.4: Dairy Coefficient Across Time

Interestingly, the *share of female decision-makers* (3) is never significant. This is not surprising in this context given that it was not significant in the Two-Way Fixed Effects model either.

Economically, results from the event-study model are largely consistent with the previous TWFE model. The TWFE model, shows overall significance, while the coefficient decomposition shows which years certain variables were more impactful, compared to the 2001 base. The same variables are significant in both models, and it seems that significant time periods from variables fit with overall trends observed in the raw data. These results have a diverse array of applicability.

Chapter 5

CONCLUDING REMARKS

5.1 Limitations and Areas for Future Research

There are a few limitations associated with this paper, namely, lack of cell phone adoption and education data and a high correlation between internet access and computer ownership.

First, data on cell phone ownership was not collected until 2021, so there is not enough data to control for that in the context of this paper. With the vast advancements of cell phone technology, one could argue that it is a substitute, in many cases, for a computer. However, the most change in the computer ownership occurs between 1997 and 2010. While cell phones were becoming more widely used, and improving in capabilities, they were not yet the do-it-all product we have today.

Another limitation is the nature of using state-level data as opposed to farm-level data. Using data aggregated to this level makes it harder to determine causality. However, using economic rationale, these results can be used to generate informed causal inferences which can be used to guide future research. For example, the proportion of dairy farms is significant and positive. From this I can only say that states more dairy farms have higher adoption levels than states with less, I cannot say that dairy farms are more likely to adopt, since I cannot directly attribute adoption.

Furthermore, education is not included in my models, even though it was shown to be consistently significant in previous studies. Due to a lack of data both relevant to my area of research and encompassing the observed time period, it could not be adequately accounted for. However, the average age of farmers increasing over time implies that there are relatively few new farmers entering the industry. In that case education would not change very much across time and would likely have a statistically insignificant effect.

Lastly, internet access and computer ownership are highly correlated. In addition, in the early periods of the dataset, most states have a higher proportion of people who own or lease computers than who have internet access. Eventually, internet access catches up and passes computer ownership. This may lead to some questions as to which is causing which. I'd make the intuitive argument that internet access is causing computer ownership and not the other way around. Information on agricultural computer use from Batte (2005) suggests that farmers do not primarily use computers for internet-necessary activities. Therefore, the difference between computer adoption and internet access could be reflecting an indifference to internet access rather than a causal relationship.

With these challenges and limitations in mind, future research could be directed in a variety of ways. First, as more data becomes available on agricultural smartphone adoption, researchers could seek to understand if the dynamics affecting smartphone adoption are the same or different than those affecting computer adoption. Similarly, further research could be done on the dynamics of significant variables. For example, what is it about dairy farms that causes them to increase overall computer adoption?

5.2 Broader Implications

Since this research was conducted at the state level, there are no causal claims about farm level adoption, rather, these results can be used to make inferences about aggregate adoption in states and regions. These results are useful in two broader contexts. The first being the technology industry. Tech companies could use these results to better market computers and computer-related products. In particular, firms in the precision agriculture industry may be interested to know about previous adoption trends and drivers, so that they can better direct their marketing efforts and identify emerging regional markets.

Furthermore, policymakers may find these results helpful. Combined with future research, these results could provide valuable information about structuring future technology policy and who to target. For example, a possible policy change may be instead of trying to encourage younger demographics to enter the industry, efforts should instead be placed in improving internet access in rural communities. This would not only broaden the market for computers, of interest to the tech industry, but could also see similar benefits to those outlined in the literature review. The broad nature of this research allows the results and implications to be used in a variety of future applications.

5.3 Conclusions

Results from the two models have many similarities to previous studies completed on farm-level computer adoption. Notable differences are the proportion of female farmers, being negatively associated with adoption and age being largely insignificant. A negative coefficient associated with price and a positive coefficient on income, though small, follow conventional economic theory and lend credence to the results. While the paper focuses on the agricultural sector, I'd expect that the results would be similar for rural communities in general.

APPENDIX A

A.1 Two-Way Fixed Effects Results with no Imputation

Table A.1: TWFE Results Using Non-Imputed Data

VARIABLES	(1)	(2)	(3)	(4)
% Dairy Farms	1.308	8.875	0.798	9.165
	(9.620)	(17.82)	(9.999)	(18.21)
Acres/Operation	2.44e-06	0.000266	2.80e-06	0.000225
	(1.19e-05)	(0.000171)	(1.17e-05)	(0.000244)
% Female	0.0702	0.474	0.0669	0.568
	(0.185)	(0.692)	(0.189)	(0.706)
% Internet Access	**0.968*** **	0.441	**0.968*** **	0.454
	(0.0750)	(0.353)	(0.0757)	(0.374)
Income ($1,000/Op.)	0.165	0.125	0.158	0.181
	(0.114)	(0.355)	(0.121)	(0.428)
Adj. CPI	**0.115*** **	0.232	0.693	1.443
	(0.0358)	(0.225)	(1.516)	(5.452)
Avg. Age	-0.134	3.935	-0.199	3.718
	(0.507)	(3.050)	(0.548)	(3.106)
State FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
# of Obs.	78	78	78	78
R-Squared	0.856	0.953	0.856	0.953

Robust standard errors in parentheses (clustered by state)
*** p<0.01, ** p<0.05, * p<0.1

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