Local Foods in Meadville: Shopping Decisions and Perceptions

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April, 2021

Submitted in fulfillment of the senior thesis requirements of the
Department of Environmental Science at Allegheny College
and approved by the senior thesis committee.

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Acknowledgements:

I would first like to acknowledge my advisors for this project, Dr. Matthew Bethurem and Dr. Kathryn Bender. You have helped me complete this process through often not ideal situations. I would also like to thank the many professors who have advised me and led me up to this point including Dr. Andrew Bloeser, Dr. Simon Bilo, Dr. Julie Wilson, Dr. Benjamin Haywood, Dr. John Golden, and Dr. Ian Carbone. All these academic influences have led me up to this point, and without any of them I doubt I would have been on the path I have found in my time at Allegheny College.

I would also like to thank my family for the support they have offered me throughout College. Specifically, my sister Maryann Ackerman, Mother Ann Ackerman, and Father Lee Ackerman. All of these people have helped me to complete college in their own ways.

I would finally like to thank my peers at Allegheny College. I have had to opportunity to meet a great variety of people who have been incredible people to experience college with. Specifically, I would like to thank Sami Landgraf, Kase Cordes, Will Harrod, Omar Moros Taylor, Ray Marszalek, Jeremiah Sullivan, and Luis Mendoza. I could not have done it without you all.

Name: George F Ackerman
Date: April 2021
Major: Environmental Studies and Economics
Thesis Committee: ***Dr. Matthew Bethurem and Dr. Kathryn Bender***

Title: Local Foods in Meadville: Shopping Decisions and Perceptions

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Food systems area subject of interest for researchers due to their importance to economic, environmental, ecological, and human health systems. This study aims to gain insight into the food system in Meadville, Pennsylvania through the lens of a sample of consumers. The survey included questions in four categories: demographics, method of food acquisition, what drives food shopping decisions, general attitudes of interest, and perceptions of local food and food more generally in Meadville. The sample is more white and richer than the Meadville population. Respondents generally had a positive view of local foods, but it seems that these views did not translate to the type of demand necessary to scale up local foods systems. Overall, the results suggest that local foods play no more than a supplemental role in food purchases, and oftentimes less than that. Results also suggest a possibility for a gap in demand for local foods and supply for local foods, especially in areas where prices for local foods are like foods produced by conventional means and where convenience of purchasing local foods can be increased.

Introduction

Food production, distribution, and consumption produce between one fifth to a third of global greenhouse gas (GHG) emissions, depending on the estimate (Vermeulen et al., 2012). These GHGs contribute to climate change which leads to several negative outcomes, according to the Intergovernmental Panel on Climate Change (IPCC, 2018). These outcomes make the way society produces food of interest to those who seek to prevent and mitigate the effects of anthropogenic climate change.

Food system can be split into the categories of conventional and alternative. Conventional food systems are an industrialized and globalized system which have increasingly led to environmental degradation, problems with human health, and a concentration of market power into fewer and fewer corporations (McMichael, 2012). Food production through contemporary food systems is of concern for human, environmental, and ecosystem health. There currently is a tradeoff between agricultural yields and the health of ecosystems and people both near to agriculture and far away (Cooper & Dobson, 2007; Van Der Werf, 1996).

Alternative systems of producing food are attempts to mitigate and eliminate some of the problems of conventional food systems. A common feature of research and practice involving alternative food systems is to buy and produce food more locally and promote the scaling up of the capacity of local food systems. This regionalization of food production is preferable through an environmental lens through less food miles, different methods of production, and less interaction with large agribusiness firms (Clendenning et al., 2016).

The benefits of local food are often categorized as environmental, economic, and social. The reduction of food miles leads to a smaller total contribution of GHGs emitted by the food system (Konieczny, 2013). This leads to less pollution associated with a local food system. The economic benefits lie in the idea that local food invigorates local economies through providing an additional source of income for residents, especially in rural areas (Obach & Tobin, 2014). Social benefits lie in the idea of civic agriculture which seeks to combine the economic, environmental, and social benefits into a system which allows for a new sense of community and care for that community (Obach and Tobin, 2014). Civic agriculture centers civic engagement within the food system, and advocates for consumers to play a role beyond the economic interaction (Bittermann, 2017). This relationship has the potential to create an effect which has

benefits for the social, environmental, and economic wellbeing of a region. Further, civic agriculture is an idea about the past in which strong agricultural communities existed, and civic agriculture has the potential to contribute to the adaptive capacity to adjust to the effects of climate change which furthers the environmental benefits (Furman et al., 2014).

A typical definition of locally produced foods is food that is grown, sold, and consumed all within a specified area that is linked geographically and culturally. There is some debate as to how close something must be to qualify, but generally a range of 50-100 miles (80-160 kilometers) is thought to qualify as locally produced (Lim and Hu, 2015). Further, the term local involves a complex interaction of factors, beyond distance, which determines how participants in local food systems define local (Trivette, 2015).

In the past thirty years, a local foods movement has emerged which aims to advocate for the purchase and increased production of local food products. On the consumer side, there are the "locavores" who are conscious consumers who are making environmentally sound purchases while supporting the local economy (Feagan, 2007; Stanton et al., 2012). To advocates, local food production represents both an opportunity to imagine better systems which benefit both consumers and producers. The local food movement has also been critiqued and questioned (Mount, 2012; Delind, 2011). The critiques include the perception that local always correlates with more environmentally friendly, overemphasis of individualism.

It is important to note that local food does not automatically equal sustainable (Coelho et al., 2018). There are possibilities that increasing the scale of local food production and systems will lead to a new set of problems, that may not necessarily be an improvement. There is also the potential for a switch to local foods which may not yield the environmental, economic or social benefits often promoted in theory.

Delind (2011), critiques the centering of the "locavore", or person who only eats local food, as a problematic feature of the local food movement. First, this term works to deflect the blame away from those in power to make change and towards individuals. Delind (2011) contests that this overemphasis plays into a fallacy that personal behavior alone can change food systems and that emphasis of the individual does little to challenge inequity. Furthermore, Delind (2011) says that the centering of locavores leads to the positioning of the individual's primary responsibility for effecting change in the world through consumption and that this diminished the

role of social and political activism needed to address the inequity and environmental problems of contemporary food systems.

Mount (2012) asks whether local food, and the values that are attached to it, are potentially scalable. Mount's (2012) analysis of research and case study leads to the conclusion that there are no easy answers to scaling up local foods, and that often the very things that create value in local food systems, such as an enhanced sense of community, are abandoned in favor of more practical logistical solutions. Mount (2012) cautions that while scaling up local food may seem favorable; it may lead to a system in which the core values are abandoned in favor of easy solutions. Mount cautions that careful planning and consideration must happen when thinking about scaling up local food, or there may be a lack of legitimacy that undermine the goals of the local food movement. The production and consumption of local foods are affected by market and policy forces which play into both the supply and demand of local foods. On the demand side, there are consumer preferences which may determine how a locally produced food is marketed to consumers and how consumers desire local foods. On the supply side there have been shifts in the competitiveness of the food market through a concentration of market power by larger firms.

Consumers have been found to be more likely to identify with food marketed based on a geopolitical boundary, for example consumers are more attracted to a product labeled as produced in their home state rather than one labeled as produced a certain distance away (Farris, 2019). Additionally, consumers are typically deterred by perceived inconvenience and unavailability of local food rather than the perception that local food is expensive (Feldman and Hamm, 2015). This perception of inconvenience lies in the idea that it would take more time for a consumer to purchase local food. Additionally, consumers are willing to pay a premium for local food, although it may depend on the type of locally produced product (Carpio and Isengildina-Massa, 2009). The ideas that consumers are willing to pay more, perceived inconvenience, and identify with geopolitical boundaries suggest methods for the scaling up of local food production. Research has also shown that consumers take part in local food systems because there is a perception that it benefits both the environment and society (Barnett et al., 2016). This suggests potential for scaling up local food to offer a more convenient shopping experience and make investments in marketing to consumers.

There has been a trend of food production to be controlled by large corporations, and a food system characterized by global markets and large, subsidized farming operations McMichael, 2012; Clendenning et al., 2016). This has led to a large supply of food, but an unequal distribution of that food. This can be seen by the levels of food waste produced in developed nations while food insecurity exists in these same nations (Lee et al., 2017). This unequal distribution has led to poor nutritional outcomes and poor environmental outcomes (Willet et al., 2019) Many advocates of local food systems, and civic agriculture, see the potential for a food system that addresses these problems. There is also an importance to integrate food issues more typically faced in cities with the rural based aspects of local food. This has the potential to increase benefits to the food systems, in sustainability and ability to adapt to climate change (Canal Vieira, 2018).

As an alternative to these globalized food systems, localized food systems have been a response which have their own set of benefits and limitations (Malak-Rawlikowska et al, 2019; Delind, 2011). While there is consumer interest in local food, much of the development of local food systems has come from intentional planning and groups which aim to improve the viability of local foods (Brown and Miller, 2008). The benefits of this planning include support from established stakeholders but is limited by the scale of action.

To encourage the development of local food systems, many have advocated for the development of food hubs. A food hub is a centralized organization which is designed as a middleman between demands of consumers and the producers of food. This enables a more streamlined supply chain which enables local food producers to sell at a larger scale. Food hubs are supported through a variety of government agencies and look to provide a way to scale up local food systems (Jablonski et al., 2016). Issues about how external pressures will act upon an alternative form of food system and the tendency towards producing for niche markets while not increasing access to low-income people are of concern when promoting the formation of food hubs (Mount, 2012; Chapman and Perkins, 2019). Food hubs also may lack the ability to transform to food systems that are needed in the context of contemporary economic conditions and the effects of climate change (Chapman et al, 2020). This is because food hub aims to integrate local food into the contemporary food system rather than develop alternative food systems.

Other ideas for better management of food systems are food policy councils. A food policy council is an organization which builds partnerships within food systems, examines food policies, and supports or creates programs that address food systems (Scherb et al., 2012). These councils typically operate at the county level of government and are sanctioned by the government jurisdiction in which they operate. Food policy councils have underlying benefits such as more democracy in food systems and a space for stakeholders to collaborate (Gupta et al., 2018). With governments sanctioning food policy councils, there is more opportunity to get citizen input when designing food policy, especially relative to contemporary food systems.

Another system often advocated for are community supported agriculture (CSA) arrangements in which community members pay a share in the food produced and receive an agreed upon amount of food on a regular basis. This helps farmers cover planting costs and have a way to create a reliable income stream (Sammogia et al., 2019). On the consumer side, a CSA member benefits from quality food and an increased relationship between the person who grows your food (Obach and Tobin, 2014). CSAs are also affected by competition which may present a weakness of the idea that CSAs always develop close relationships with consumers and farmers (Galt et al., 2016). This competition undermines the goals of a CSA as an alternative way to get food because when farms compete profits are reduced, and there can be a lost sense of community. CSAs have benefits and limitations but provide a way for farmers to sell to local consumers with a reliable income. Additionally, CSA members are typically wealthier relative to non-members (Russel and Zepeda, 2008). This may mean that increased adoption of CSAs may lead to increased disparity that is already present in contemporary food systems.

Civic agriculture is an idea that many advocates of local food systems find compelling. This is because the ideas behind civic agriculture address the social, economic, and environmental benefits of a local food system (Obach & Tobin, 2014). In its ideal form, civic agriculture can be an effective tool in reinvigorating communities who have seen disinvestment and stagnant local economies. The idea of civic agriculture is linked to the push for local food systems, food hubs, and CSAs. It provides consumers with opportunities to connect with who produces their food, presents an opportunity for rural economic development, and has the side effect of producing food systems which have lower emissions (Vermeulen et al., 2012). Civic agriculture presents an opportunity to make community-based change on food systems because it emphasizes the interconnectedness of community and local food production (Trauger et al.,

2010). Food systems contain tradeoffs and unknowns, but also offer potential solutions to the problems of contemporary food systems. It would be wrong to dismiss CSAs and Food Hubs, but those interested in better food policy should recognize and work to mitigate the aspects of each that have led to valid criticisms considering the overall goal of increased sustainability in food systems and mitigating the problems of the contemporary food system.

The utility of food is often included in attempts to measure consumer's reasoning for selection of certain types of food. Research has suggested the consumers participate in alternative food networks, like local food systems, mostly due to the benefits provided to society and the environment (Barnett et al., 2016). This suggests that those who choose to participate in consuming from local food are receiving an additional benefit from the utility gained from the benefits of participating in these systems. Additionally, there is a general increase in the demand for local food meaning that consumers are willing to pay more for an increase in utility derived from societal and environmental benefits.

In the United States, the typical consumer of local food is wealthier, and of higher socioeconomic status relative to the average American (Bir et al., 2019). This suggests that local food is a luxury good, or a good whose consumption increases as a consumer's income increases. This is because local food is often of higher quality, higher price, and comes with increased barriers to access for those of lower socioeconomic status. As such, the presence of a luxury good comes with many considerations.

Additionally, lack of capital investment has been a problem among local food producers who wish to scale up supply to meet demand (Day-Farnsworth, 2009). These capital investments include things like refrigeration, vehicles, and better agricultural equipment. This is an area in which the scaling up of the capacity of local food systems could play a role in lifting up the potential of local food systems, and further the potential of benefits from the use of alterative food systems.

The purpose of this research is to better understand the mechanisms of consumer preferences and decision making around local foods in the city of Meadville, Pennsylvania. Meadville was selected as the area of interest for a survey aiming to understand consumer preferences and perceptions of local foods. Meadville is situated in Northwestern Pennsylvania and is the county seat of Crawford County.

As of 2017, there are around 1,000 farms in Crawford County with an average size of 178 acres. Crawford County has seen a decrease in the number of farms from almost 1500 in 2007 to a little over 1000 in 2017. There has also been an increase in the size of these farms and increases in per farm average of the market value of products sold (USDA, 2012; USDA, 2017).

Meadville also has a local foods vendor, known as the Market House, which is run by a local government authority. The Market House aims to provide local, sustainable foods while connecting the public with local food producers. Meadville also has locally owned grocery stores, regional supermarket chains such as Giant Eagle and Tops, and larger chains including Walmart and Aldi. There are also many take-out, restaurant, and fast-food options. This study aims to better understand how the people of Meadville make decisions when shopping for food, and what they think about local food.

Methods

The survey was distributed through two methods, online and mail based. The online portion of the survey was conducted using Qualtrics survey software. The mail-based survey was distributed through the United States Postal Service to 300 homes in Meadville, Pennsylvania. The survey was also limited to people living within the City of Meadville. Both versions of the survey asked the same questions and were in similar formats.

The survey consisted of six sections. First, participants were screened to ensure that respondents fit the target demographics and necessary limits of the survey, like being over 18. Demographic data was collected. This included age, ethnicity, race, gender, marital status, approximate yearly, household income range, highest education level, and number of people who got the majority of their meals within the household. The remaining sections utilized 5-point Likert scale questions. These sections included food acquisition attributes, food shopping preferences, general attitudes, and perceptions of the food system in Meadville. The survey was constructed in this manner to begin with more general information about food shopping habits, take a break from food when asking about general attitudes, then return to more focused questions about specific perceptions of food in Meadville.

Survey questions were informed from previous studies on food shopping habits and research on perceptions of local food. The questions on the methods of food acquisition were

inspired by a technical report from the Ohio State University (OSU) Food Waste Collaborative, titled “The State of the American Refrigerator: July 2020 Survey” (Bender et al., 2020).

Nilsson et al (2014) surveyed consumers in Sweden to understand the relationship between demographics, type of grocery shopping and store format characteristics. This study informed questions around food acquisition methods and demographics.

Farris et al. (2019) surveyed consumers to understand how geographic distance and attachment value work in the market for hard cider. This informed questions which sought to measure whether respondents valued food produced locally.

Stanton et al. (2012) surveyed primary food shoppers in Pennsylvania households to understand what those who shop for local foods value when making these decisions. This was used to inform questions about what food shoppers look for when making shopping decisions. Questions were also informed by a general sense of the consumer side of the Meadville food system.

The electronic survey was created and housed in a protected Qualtrics survey platform, and was distributed in two ways: First, a link to the survey posted on the public Facebook pages of FYI Crawford County and MyMeadville. These pages were selected due to the popularity of FYI Crawford County as a private group with 27,000 members, and FYI Crawford’s County’s focus on communicating local information relevant to residents of Meadville, PA. MyMeadville was selected to post the survey due to this history of gathering perceptions of the people of Meadville. The posts consisted of a short solicitation statement and the link to the survey.

Second, a flier with a scannable QR code that links to the survey was posted on physical bulletin boards at the Meadville Area Recreation Center, the Meadville YMCA, the Meadville public library, and the Downtown Meadville Mall. These locations were chosen due to being common public spaces in Meadville City limits as well as their geographical distribution throughout town. This method enabled those who may not be as active in the Facebook groups, but may be more active in the physical spaces of Meadville to take the survey.

Hard copies of the survey were mailed to the 300 randomly selected homes within the city limits of Meadville with a hard copy of the survey and a return envelope. This necessitated the purchase of one standard forever stamp as well as an “additional ounce” stamp due to the weight of the envelope. To acquire mailing addresses, the sire directmail.com was used. A

random selection of 1,000 household addresses from a list of all the homes in the 16335-zip code was purchased. The RAND function in Microsoft Excel was used to randomize the 1,000 addresses and select 300 randomly. Some addresses were filtered out due to not being in the city limits of Meadville, but still having the same zip code. Addresses which were filtered out were replaced with valid Meadville addresses. Surveys were mailed out on January 25th, 2021 and the return period lasted for three weeks. After the cut off, returned surveys were disposed of.

To analyze the survey data, Stata 13 software was used. Due to the ordered ranking of the Likert questions, an ordered logistic regression model was used for analysis. The ordinal logistic regression was conducted to estimate the ordinal outcome variables from a set of independent variables. The empirical analysis aspect included analyzing summary statistics as well as ordered logistic regression. The ordered logistic regressions used income, age, highest education level household size, and the general attitude questions as dependent variables of interest.

Results

The online-based survey received 407 responses and 42 mail-based surveys were returned. There were 278 usable responses from the online survey and 32 from the mail-based survey, for a total of 300 responses. Responses were eliminated due to lack of completeness, failure to provide informed consent documentation, and mail-based surveys that were returned after the cut off. Of the 300 responses, there were 276 completed surveys and 24 partially completed surveys. Of the partially completed surveys, many were only missing a few data points. Each included variable has over 290 response data points, with many having 299 or 300. This means that there is some missing data, but many of the questions were answered by almost all of the respondents included in the final data set. For example, there were only 290 responses for income, but those who skipped this question often answers many other questions. This partially filled data was included, so that the most amount of information was included and to not waste data. The tables below include the number of respondants for each equation. The STATA software automatically eliminates partially incomplete variables leading to regressions often having between 276 and 290 observations.

Demographic data is included in Table 1. Overall, the sample is more white and wealthier than the population of the City of Meadville. There were more respondents which reported

yearly income as over $100,000 than any other category. 83% of the included survey respondants identified as female. The sample consisted of a majority of respondents that had at least some experience with higher education with 80% having above a High School/GED education level.

71.33% responded that they are the main shoppers of their household, with 5.67% saying they did more than75% of the shopping, 13.67% saying they did 50% of the shopping, and 9.33% saying they did less than 50% of the shopping for their household. The average number of people getting most of their meals from the respondent's home was 2.94.

Table 1: Demographic data

Income	Frequency	Percent
$0-10,000	10	3.39%
$10,001-20,000	21	7.12%
$20,001-30,000	27	9.15%
$30,001-40,000	37	12.54%
$40,001-50,000	38	12.88%
$50,001-70,000	40	13.56%
$71,000-85,000	35	11.86%
$85,001-100,000	33	11.19%
$100,001+	54	18.31%
Total	295	
Marital Status	**Frequency**	**Percent**
Single	60	20%
Married	179	59.67%
Domestic Partnership	21	7%
Divorced	20	6.67%
Widowed	15	5%
Separated	5	1.67%
Total	300	
Age	**Frequency**	**Percent**
18-24	23	7.67%
25-30	35	11.67%
31-40	67	22.33%
41-50	57	19%
51-65	86	28.67%
65-80	30	10%
80+	2	0.67%
Total	300	
Highest Education Level	**Frequency**	**Percentage**

Some High School	4	1.33%
High School Degree/GED	56	18.67%
Trade School	21	7.00%
Some College	64	21.33%
Associate's Degree	36	12.00%
Bachelor's Degree	78	26.00%
Master's Degree	36	12.00%
Doctoral Degree	5	1.67%
Total	300	
Race	**Frequency**	**Percent**
white	282	95.92%
Black or African American	4	1.36%
Native Hawaiian or Pacific Islander	2	0.68%
American Indian or Alaska Native, white	5	1.70%
Black or African American, white	1	0.34%
Total	294	
Household Size (Based on meals from home)	**Frequency**	**Percent**
1	33	11.00%
2	102	34.00%
3	73	24.33%
4	57	19.00%
5	20	6.67%
6	8	2.67%
7+	7	2.33%
Total	300	
Gender	**Frequency**	**Percent**
Female	249	83%
Male	47	15.67%
Non binary	1	0.33%
Prefer not to say	2	0.67%
Other	1	0.33%
Total	300	

Table 2- Food acquisition attributes

Most common type of store used to acquire food/groceries	**Frequency**	**Percent**
Supermarket	88	30.34%
Grocery Store	160	55.17%
Locally Owned Grocery Store	33	11.38%

Fast Food	1	0.34%
Locally Produced Food Provider	3	1.03%
Takeout/Delivery	1	0.34%
Other	4	1.38%
Total	290	
Method of travel to acquire food/groceries	**Frequency**	**Percent**
Personal or Household Motor Vehicle	288	96.64%
Public Transportation	1	0.34%
Another Person's Vehicle	4	1.34%
Walking	3	1.01%
Other	2	0.67%
Total	298	
Method of food acquisition	**Frequency**	**Percent**
Buy in Person	244	81.61%
Grocery Delivery	13	4.35%
Pick up preordered food	40	13.38%
Other	2	0.67%
Total	299	
How frequently grocery shopping is done	**Frequency**	**Percent**
Every few days	46	15.33%
Weekly	182	60.67%
Every two weeks	63	21.00%
Once a month	8	2.67%
Not applicable	1	0.33%
Total	300	

Generally, survey respondents had a favorable view of locally produced food. Around 79% of respondents perceived local foods as being better for the environment, and 85% perceived local food as being “probably or definitely” of better quality than non-local food. 71.9% of respondents said that they cared about knowing where their food came from.

Summary statistics show a gap in the reported value of local food when making a shopping decision and the most used store. 54% said the presence of local food had a positive effect when making a food shopping decision. Most respondents mainly shopped at traditional grocery stores (51.77%) and supermarkets (30.34%), with just three respondants mainly shopping at a local food vendor. Additionally, a majority of respondents perceived local food as “probably or definitely” more expensive than non-local foods, and a majority of respondents perceived local food as harder to access than other foods.

Respondents clearly cared the most about quality and price when shopping for food/groceries. These two categories had the largest proportion of the highest level of agreement. Respondents also signaled that they cared about variety, nutrition, whether a product was produced in the USA, store familiarity, convenience of the shopping experience, and convenience of travel to the store, local food availability, and availability of products other than food. For each of these variables, over 50% of respondents said that they mattered either "a great deal" or "a lot".

Aspects that did not matter to respondents were the availability of food assistance, like SNAP or WIC, the availability of organic food, the possibility of running into a friend while shopping, the animal welfare aspect of food production, and the environmental effects of food production. Each of these variables had less than 50% say that they mattered either "a great deal" or "a lot" when making shopping decisions.

A set of four questions was asked to see if respondents preferred a regional label, like Northwest Pennsylvania, or a mileage distance, like within 50 miles of where they live. The questions included the categories of Western Pennsylvania or Eastern Ohio, Northwest Pennsylvania, within 50 miles of where they live, or within 100 miles of where they live. Northwest Pennsylvania as a regional distinction, and 50 miles as a representation of distance from home represent approximately the same level of locality. Western Pennsylvania or Eastern Ohio as a regional distinction, and 100 miles as a representation of distance from hope represent approximately the same level of locality. Respondents did respond more favorably to the geographic labels rather than the simple distance ones; the difference was only about a 4% increase in responses saying the geographic labels mattered a great deal when making shopping decisions compared to the corresponding mile distance labels. For each of the geographic and distance labels, over 50% of respondents said that these factors played a positive role in their shopping decisions.

Table 3- Questions about how much the respondents have valued the category when making shopping decisions in the past two months.

	A great deal	A lot	Indifferent	A little	Not at all
Price (n=299)	44.82% (134)	38.13% (114)	7.36% (22)	8.03% (24)	1.67% (5)
Quality (n=294)	53.06% (156)	42.88% (129)	2.72% (8)	0.34% (1)	0% (0)

Variety (n=297)	31.65% (94)	47.81% (142)	15.82% (47)	4.71% (14)	0% (0)
Nutrition (n=298)	32.21% (96)	42.28% (126)	20.13% (60)	4.36% (13)	1.01% (3)
Familiarity With Store (n=298)	32.21% (96)	37.58% (112)	23.49% (70)	3.02% (9)	3.69% (11)
Availability of SNAP and/or WIC purchase options (n=299)	7.36% (22)	5.02% (15)	13.38% (40)	2.68% (8)	71.57% (214)
Convenience of shopping experience (n=300)	24.67% (74)	48.33% (145)	16% (48)	9% (27)	2% (6)
Convenience of travel to food/grocery store (n=297)	20.20% (60)	39.39% (117)	28.62% (85)	7.74% (23)	4.04% (12)
Availability of locally produced food (n=300)	19.33% (58)	34.67% (104)	26% (78)	14.67% (44)	5.33% (16)
Availability of organic food options (n=299)	8.70% (26)	10.03% (30)	30.10% (90)	15.38% (46)	35.79% (107)
Availability of products other than food (n=298)	24.83% (74)	26.85% (80)	22.82% (68)	17.45% (52)	8.05% (24)
Possibility of running into a friend (n=300)	4% (12)	6.67% (20)	43.33% (130)	7.67% (23)	38.33% (115)
Animal welfare aspects of food production (n=299)	12.04% (36)	26.09% (78)	26.09% (78)	17.39% (52)	18.39% (55)
Environmental effects of food production (n=298)	13.09% (39)	27.85% (83)	29.53% (88)	16.11% (48)	13.42% (40)
Knowing that a food purchase is produced within the Western Pennsylvania and Eastern Ohio region (n=296)	14.86% (44)	19.93% (59)	26.69% (79)	29.05% (86)	9.46% (28)
Knowing that a food purchase is produced in Northwestern Pennsylvania (n=297)	15.82% (47)	23.23% (69)	28.62% (85)	22.56% (67)	9.76% (29)
Knowing a food purchase is produced somewhere within 50 miles of your home (n=297)	10.77% (32)	24.24% (72)	31.65% (94)	20.54% (61)	12.79% (38)
Knowing a food purchase is produced somewhere within 100 miles of your home (n=297)	11.11% (33)	23.57% (70)	32.66% (97)	21.89% (65)	10.77% (32)
Knowing that a food purchase was produced in the United States of America (n=298)	33.89% (101)	37.92% (113)	14.09% (42)	10.07% (30)	4.03% (12)

In terms of food availability and food quality, a majority of respondents (58.33% and 62.21%, respectively) either slightly or strongly agreed that these two aspects of the food system were adequate in Meadville.

Care for the strength of the local economy and care for the environment ranked as the most agreed upon elements of the 'general attitudes' section among the respondents. Over 95% said that they cared about the strength of the local economy and just under 95% of respondents said that they cared about the environment. Respondents generally agreed that they felt they were a part of a larger community in Meadville, with 54.4% strongly or slightly agreeing that they felt this way and 30.77% neither agreeing nor disagreeing with this. Respondents reported being involved in their community, with 65% saying they either strongly or slightly agreed with the statement, "I am involved in my community". Respondents were generally willing to pay more for goods and services if they knew it would help someone in the Meadville community. 40% of respondents strongly agreed with this statement and 44.67% slightly agreed. Most respondents agreed that climate change is a problem, with 71.24% either strongly or slightly agreeing with that statement. Respondents had a similar amount of agreement with the statement, "I care about knowing where my food comes from", with 71.91% saying they either slightly or strongly agreed.

Table 4- Perceptions of local foods and food access in Meadville

	Definitely Yes	Probably Yes	Unsure	Probably not	Definitely not
Do you think locally produced food is usually of better quality than what is found in supermarkets? (n=299)	43.14% (129)	41.47% (124)	12.37% (37)	2.68% (8)	0.33% (1)
Do you think locally produced food is usually better for the environment than food at supermarkets? (n=300)	39.67% (119)	38.33 (115)	18.33% (55)	3.33 (10)	0.33% (1)
Do you think that purchasing food from your most commonly used type of food provider is the most convenient way to purchase food for your family? (n=300)	41% (123)	46% (138)	8% (24)	4.33% (13)	0.67% (2)
Do you think that purchasing food from your most commonly used type of food provider provides you with the best nutritional value for your family? (n=300)	11% (33)	38.33% (115)	24% (72)	25.67% (77)	1% (3)

Do you think that purchasing food from your most commonly used type of food provider provides the best value for your money? (n=300)	25.33% (76)	43.67% (131)	17% (51)	12.33% (37)	1.67% (5)
Do you feel locally produced food is more expensive than other foods? (n=298)	24.16% (72)	40.60 (121)	27.18% (81)	6.71% (20)	1.34% (4)
Do you feel locally produced food is harder to access than other foods? (n=299)	24.41% (73)	31.77% (95)	26.42% (79)	14.72% (44)	2.68% (8)
Do you feel that food availability in Meadville is satisfactory? (n=300)	16% (48)	42.33% (127)	20% (60)	14.67% (44)	7% (21)
Do you feel that the availability of locally produced food in Meadville is satisfactory? (n=299)	8.72% (26)	33.22% (99)	22.82% (68)	27.18% (81)	8.05% (24)
Do you feel that the quality of available food in Meadville is satisfactory? (n=299)	24.16% (72)	47.83% (143)	18.73% (56)	16.39% (49)	2.68% (8)

Table 5- General Attitudes

	Strongly Agree	Slightly Agree	Neither Agree or Disagree	Somewhat Disagree	Strongly Disagree
I care about the environment (n=299)	58.19% (174)	35.12% (105)	5.68% (17)	0.67% (2)	0.33% (1)
I am involved in my community (n=300)	24% (72)	41%(123)	25.67% (77)	4.67% (14)	4.67% (14)
I feel a part of a larger community in Meadville (n=299)	20.40% (61)	34.11% (102)	30.77% (92)	5.35% (16)	9.36% (28)
I care about knowing where my food comes from (n=299)	32.44% (97)	39.46% (118)	23.75% (71)	3.68% (11)	0.67% (2)
I believe climate change is a problem (n=299)	45.15% (135)	26.09% (78)	17.39% (52)	5.35% (16)	6.02% (18)
I care about the strength of the local economy (n=300)	70% (210)	25.67% (77)	4% (12)	0% (0)	0.33% (1)
I am willing to pay more for goods and services if it helps someone in my community (n=300)	40% (120)	44.67% (134)	9.67% (29)	3.67% (11)	2% (6)

Table 6- COVID-19 Pandemic's effects on shopping habits

How much the COVID-19 Pandemic has changed shopping habits?	Frequency	Percent
A great deal	28	16.16%
A lot	61	20.54%
A moderate amount	108	36.36%
A little	53	17.85%
None at all	27	9.09%
Total	297	

Ordered logistic regression analysis was done to answer three questions:

1. How does changes in the level of income, age, highest education level, and household size affect different perceptions of local food?
2. How does changes in the level of income, age, highest education level, and household size affect reported food shopping preferences?
3. Do changes in the level of income, age, highest education level, and household size affect general perceptions about community, the environment, and the local economy, which may shed light on possibilities for civic agriculture?

For the results of these questions, specified variables were selected as variables of interest. These variables demonstrated levels of statistical significance, which allows for more reliable interpretation. Full results of the regression analysis are available in tables below. There were also variables that were statistically significant, but not of high value to the interpretation of these results, so they were omitted.

Likert scale results were coded as 1 equaling the highest level of agreement, and 5 equaling the lowest level of agreement. As ordered logistic regression results are typically reported as odds ratios this means that an odds ratio above 1 lead to an increased odds of being above the particular categories which were the higher levels of agreement, and an odds ratio below 1 meaning that there is a lower odds of being above the high levels of agreement. In other words, an above 1 odds ratio corresponds to increased odds of disagreeing or not caring about the variable, and a below 1 corresponds to decreased odds of disagreeing or not caring about the variable. Additionally, the variables reported below apply when all other independent variables in the model are held constant.

Demographic influence on local food

An ordered logistic regression was used to gain insight into the effects of income, age, highest education level, and household size on perceptions of local food. Five regressions were used to examine the effects of income, age, and highest education level as the independent variables. The dependent variables used in this model were the extent to which the availability of local food affected shopping decisions, the set of four geographic and distance labels, perceptions of the availability of local foods in Meadville, perceptions of how expensive local food was, if locally produced food is perceived as higher quality than alternatives, and the perception of local foods as better for the environment. Tables for the regressions are in the appendix under "Question 1 regressions."

For the dependent variable of if local food availability affected shopping decisions, age had a odds ratio of 0.83, a p-value of 0.010 which was significant at the 5% level. This shows that for each increasing level of age category there are lower odds of not valuing local foods when making a shopping decision. Older people have a higher odds of valuing local foods when they made a shopping decision in the previous two months before taking the survey.

For the dependent variable of perception of access to local food, age had an odds ratio of 1.14, and a p-value of 0.084 which was significant at the 10% level. This means that a one unit increase in age level increases the odds of thinking local foods are less available. In other words, older people had higher odds of viewing local food as satisfactorily available in Meadville.

For the dependent variable of if local food is more expensive than other foods, age had an odds ratio of 1.20, had a p-value of 0.017 which was significant at the 5% level. This means that a one unit increase in age level increases the odds of agreeing less that local foods are more expensive than other food options.

Income also was significant in this question. Income affected if availability of local food affected shopping decisions and the perception of local food having increased quality.

For the dependent variable of caring about the availability of local food, the odds ratio for income was 1.15, had p-value of 0.004, and was significant at the 1% level. This means that an increase in income level leads to an expected increase in being above the "A great deal" level of response. In other words, increased income may result in caring less about the availability of local foods when making shopping decisions.

For the dependent variable of local food being perceived as more quality than other foods, the odds ratio for income was 1.17, had a p-value of 0.04 and was significant at the 1% level. So, as income level rises there are higher odds of perceiving local foods as not of superior quality than other foods.

Demographic influence on reported food shopping preferences

An ordered logistic regression was also used to understand the relationship between the selected demographic variables and reported shopping preferences. Eighteen regressions were run to understand this relationship. The independent variables were income, age, education, and household size. Dependent variables included all the variables which contributed to shopping decisions in the past two months. These variables were price, quality, variety, store familiarity, availability of food assistance programs, convenience of shopping experience, convenience of travel to store, availability of local food, availability of organic food, availability of items other than food, possibility of running into a friend, the animal welfare aspects of food production, the environmental effects of food production, whether a food product was produced in Western Pennsylvania or Eastern Ohio, whether a food product was produced in Northwest Pennsylvania, whether a food product was produced within 50 miles on the place a respondent lived, whether a food product was produced within 100 miles of the place a respondent lived, and if a food product was produced in the United States. Tables for the regressions are in the appendix under "Question 2 regressions."

For the dependent variable of how much price mattered, the odds ratio for income was 1.29, had a p-value of less than 0.0005, and was significant at the 1% level. This shows that as the level of income increased, the odds of caring about price "a great deal" were decreased. In other words, increased income led to respondants having a higher odds ratio of not caring as much about price when making a shopping decision.

Income level also was highly significant for if the availability of food assistance programs matters when making a shopping decision. For income, the odds ratio was 1.47, the p-value was less than 0.0005, which made it significant at the 1% level. So, a one level increase in income increases the odds of caring less about food assistance by 47%.

Income level also had a strong effect on if the environmental effects of a food purchase mattered. The odds ratio was 1.23, the p-value was less than 0.0005, which made it significant at

the 1% level. So, as income level increased there was a higher odds of caring less about the environmental impact of a food purchase.

Income also had a strong effect on caring about if the food was regionally produced. For the dependent variable of knowing region of production and knowing the distance a food purchase was produced within in relation to the respondent's home mattered when making shopping decisions, the odds ratios were consistent across the different subcategories. For Western Pennsylvania and East Ohio, the income odds ratio was 1.15, the p-value was 0.006 and was significant at the 1% level. For Northwest Pennsylvania, the income odds ratio was 1.16, the p-value was 0.004, and was significant at the 1% level. For within 50 miles, the income odds ratio was 1.18, the p-value was 0.001 and was significant at the 1% level. For within 100 miles, the income odds ratio was 1.17, the p-value was 0.002 and was significant at the 1% level. This all shows that as level of income rises, there are higher odds of caring less about whether food was produced locally.

Age was also an independent variable of interest as it had effects on how variety of food options affected shopping decisions, how the availability of food assistance affected shopping decisions, how the convenience of the shopping experience affected shopping decisions, and how the convenience of travel affected shopping decisions.

For the dependent variable of how the variety of available food options affected food shopping decisions, age had an odds ratio of 0.80, a p-value of 0.006, and was significant at the 1% level. So, as level of age increases the odds of caring about variety are higher.

For the dependent variable of how the availability of food assistance affected shopping decisions, the age odds ratio was 1.21, had a p-value of 0.040, and was significant at the 5% level. This shows that as the level of age increases, there is higher odds of caring less about availability of food assistance.

For the dependent variable of how convenience of shopping experience affected shopping decisions, the age odds ratio was 0.86, had a p-value of 0.064 and was significant at the 10% level. So, as level of age increases there is a higher odds ratio of caring about convenience. In other words, a one level increase in age corresponds to a 14% decrease in the odds of being above the category of convenience mattering "a great deal."

Demographic influences on civic agriculture indicators

An ordered logistic regression was also used for this question. The independent variables included income, age, education, and household size. The dependent variables included several statements that constituted the general attitudes section of the survey. These statements were:

- "I care about the environment"
- "I believe climate change is a problem"
- "I care about the strength of the local economy"
- "I care about knowing where my food comes from"
- "I am involved in my community"
- "I feel a part of a larger community in Meadville"
- "I am willing to pay more for goods and services if it helps someone in my community"

There were seven regressions run to understand the relationships between certain demographics and these general attitudes. Tables for the regressions are in the appendix under "Question 3 regressions"

Age and income were again the variables that had the highest levels of statistical significance. For income, the statements about caring about the environment and caring about knowing where food came from were of interest.

For the dependent variable of caring about the environment, the income odds ratio was 1.13, the p-value was 0.039, and was significant at the 5% level. So, as level of income increases there are higher odds of having a lower level of agreement with the statement "I care about the environment."

For the dependent variable of caring about knowing where food came from, the income odds ratio was 1.19, the p-value was 0.001 and age was significant at the 1% level. So, as the level of income increases there are higher odds of having a lower level of agreement with the statement "I care about knowing where my food comes from."

For the independent variable age, caring about the strength of the local economy and knowing where food came from were variables of interest.

For the dependent variable of caring about the strength of the local economy, the age odds ratio was 0.82, the p-value was 0.028, and age was significant at the 5% level. So, as level of age increases, there are higher odds of strongly agreeing with the statement "I care about the strength of the local economy."

For the dependent variable of knowing where food came from, the age odds ratio was 0.87, a p-value of 0.083 and age was significant at the 10% level. So, an increase in the level of age corresponds with higher odds of agreeing with the statement “I care about knowing where my food comes from.”

Table 7- Regression Results

Demographic Influence on Local Food			
Independent Variable	Dependent Variable	Odds Ratio	P-Value
Age	Local Food Availability Affecting Shopping Decisions	1.14	0.084
Age	Local Food is More Expensive Than Other Foods	1.21	0.017
Income	Local Food Availability Affecting Shopping Decisions	1.15	0.004
Income	Local Food Is More Quality Than Other Foods	1.17	0.04
Demographic Influence On Reported Food Shopping Preferences			
Independent Variable	Dependent Variable	Odds Ratio	P-Value
Income	Price	1.29	>0.0005
Income	Availability of Food Assistance Programs	1.47	>0.0005
Income	Environmental Effects of Food Purchase	1.23	>0.0005
Income	Food Produced in Western Pennsylvania or Eastern Ohio	1.15	0.006
Income	Food Produced in Northwest Pennsylvania	1.16	0.004
Income	Food Produced Within 100 Miles	1.18	0.001
Income	Food Produced within 50 Miles	1.17	0.002
Age	Availability of Food Assistance Programs	1.21	0.04
Age	Convenience of shopping experience	0.86	0.064
Demographic Influences on Civic Agriculture Indicators			
Independent Variable	Dependent Variable	Odds Ratio	P-Value
Income	"I care about the environment"	1.13	0.039

Income	"I care about knowing where my food comes from"	1.19	0.001
Age	"I care about the strength of the local economy"	0.82	0.028
Age	"I care about knowing where my food comes from"	0.87	0.083

Discussion

This survey begins to take inventory of the shopping habits of residents of the City of Meadville, Pennsylvania. There are gaps unfilled by this study that exist and provide an opportunity for further research. Mainly, the results of this survey have implications for understanding the food system for a sample of 300 people. These results both confirm and challenge previous research on local food systems. The summary statistics data are useful for understanding what motivates shopping decisions and perceptions of local food. The three regressions present some information on how income and age affect perceptions of local food.

There are limitations that apply to interpretations of the data produced from this survey. First, is that the sample is different in demographics than the general Meadville population, specifically the income, race, and gender variables represent this. Additionally, the sample was not randomly selected. This creates problems with statistical interpretation, and limitation in applying the survey data to the population of Meadville. The survey was also conducted during the COVID-19 pandemic, which affected things like shopping for food in a significant way. This is seen in the question about how much the pandemic has affected respondent's shopping habits. This may lead to these results being relatively unique and perhaps not replicable due to the unusual circumstances that have affected the way people shop for food.

Consumers had more favorable perceptions of a food which is labeled with a regional label instead of a distance. This confirms previous research by Farris et al. (2019) The "Northwest Pennsylvania" and "Western Pennsylvania or Eastern Ohio" variables had higher levels of mattering a "great deal" than corresponding distance-based descriptions which were "Within 50 miles of where you live" and "Within 100 miles of where you live". There were about 4% more respondents saying it mattered a great deal when regional labels were the variable. Further, the results suggest that a food product labeled as being produced in the United States had the largest number of responses that were favorable. These results suggest that

products should be labeled as produced in Northwestern Pennsylvania or other regional labels compared to using distance-based labeling. McClusky and Loureiro (2003) investigated several types of food labels and found that consumers must perceive a product as high quality to pay a premium for it. Future studies could look at how the label "PA Preferred", which is a label given out by the Pennsylvania state government, affects shopping decisions, or willingness to pay.

Summary statistics also suggest implications for how to market locally produced products. Respondents responded favorably to the question about willingness to pay more if it helped a member of the community. Many local foods markets have utilized profiles of the producers of available food. These profiles often include information including the farmer's name, the farm's name, information about farming practices, or history of the farm. These results suggest the potential for adding detail to these profiles, holding events to further foster connection between consumers and producers, and the use of spaces and structures for the connection between producers and the community. Park (2018) found that consumers are more willing to pay for socks if there was a human welfare narrative involved, which lends support to emphasizing how purchasing a product would help the welfare of local farmers. Brown (2003) found that local foods marketing should include information about quality, price and appeal to environmentalists who are more likely to support local foods. This supports the findings that consumers cared a lot about quality and price when making shipping decisions. In the framework of civic agriculture, the potential for a deeper connection between local producers and those who perceive local foods favorably, may exist.

There is also potential for the increased emphasis on the environmental and climate benefits of locally produced food. A majority of the respondants agreed that they cared about the environment and that climate change is a problem. This creates an opportunity for local food to increase its viability by emphasizing the climate and environmental benefits of local food. This fact, coupled with the generally positive perceptions of local food provides opportunity for CSAs, farmers markets, and other local food providers to emphasize the environmental and climate benefits of locally produced food (Park, 2018).

The ordinal logistic regression analysis had two main conclusions. First, increases in the reported level of income typically caused increases in caring less about local foods, environmental effects of food production, and were more likely to care less about the

environment. Second, age typically corresponded to higher levels of valuing local foods and caring about the local economy.

Respondent's preferences surrounding local foods decreased as the levels of income increased. This calls into question some previous research about the idea of "locavores" who are commonly wealthier (Bir et al., 2019; Feldman and Hamm, 2015). It also suggests that in this sample, people of lower income value the presence of local foods more. This suggests that the sample may be different than expected due to error in the study, or Meadville being a unique market for food.

Age was also a variable that affected the role of local foods in Meadville's food system. It seems that those of older age levels were generally in positions that made them care less about the presence of local foods. People of higher ages generally cared more about things like food assistance than other age groups. Also, people of higher age were more likely to see local foods are more expensive than other foods. Another key attribute was that people of higher age did not particularly care about convenience related aspects when making decisions about food shopping. This leads to a possibility for local foods, which are generally perceived as less convenient.

The results of the survey have begun to understand how people in Meadville shop for their food and the role local food plays in the Meadville food system. As mentioned above, the results of this survey are limited and present multiple opportunities for future research.

This survey attempted to understand the local foods market through the lens of potential consumers. To gain more understanding into the local foods system in Meadville research could be done on the entire local foods system instead of only a part of it. This would lead to a more holistic understanding that would have increased ability to make evidenced based policy decisions.

In terms of better understanding what consumers think, a future survey could have a narrower focus on local foods issues. While this survey was designed to ascertain actions and perceptions around local foods there was also a lot of background questions involving attributes that may not as directly affect the market for local foods. Additionally, this survey missed an opportunity to understand the amount of shopping which happens at local foods vendors in Meadville. A future survey could ask about the frequency in which local food is purchased, if these purchases mainly involve farmers markets, CSAs, or other local food vendors such as the Market House and looking at specific locally produced products such as types of meat and

vegetables that consumers prefer. Through specifically understanding what percentage of food people get from local vendors and gaining more information on the local foods market in Meadville, a more complete picture of the market can be ascertained.

There is also the potential for more detailed information through other means of data collection, like interviews or focus groups. While the numbers of the data may be limited, there is potential for increased insight into the factor which affect decisions and perceptions around the market for local foods in Meadville.

Conclusion

This survey begins to understand the market for local foods in Meadville, Pennsylvania. There are key aspects which suggest a potential for the growth of the local foods systems, mostly that those of lower income level may be a key demographic along with older people in Meadville. Additionally, people do have favorable views of local food, and report that local food matters when making shopping decisions, but often do not act on this when selecting a main place to shop for food or groceries. This suggest that a regional food hub may be of use to get more local food into where consumers already commonly shop. Additionally, Meadville may be a good place for enacting the civic agriculture framework as respondants responded positively to questions about caring about the environment, local economy, caring about knowing where their food came from, and signaled willingness to pay more if they knew it would help a member of their community. Despite this, scaling up local food and advocacy for locally produced products, should be done intentionally and with caution not to simple assimilate into the larger systems of problematic food production. Local food may not be an answer to the large-scale reduction of GHGs associated with the food system, but there are potential economic, environmental, and social benefits of improving local food systems.

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Appendix:

Question 1 Regressions:

```
. ologit LocalFoodAvail_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -434.59796
Iteration 1:   log likelihood = -424.86046
Iteration 2:   log likelihood = -424.81276
Iteration 3:   log likelihood = -424.81275

Ordered logistic regression                     Number of obs   =        295
                                                LR chi2(4)      =      19.57
                                                Prob > chi2     =     0.0006
Log likelihood = -424.81275                     Pseudo R2       =     0.0225

------------------------------------------------------------------------------
LocalFoodAvail_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
       Income_n |   1.159051   .0591981     2.89   0.004     1.048644    1.281084
         Age_n |   .8200393   .0631502    -2.58   0.010     .7051552    .9536403
        Educ_n |   1.062435   .0729068     0.88   0.377     .9287331    1.215385
    HouseSize_n |   .9603994   .0796281    -0.49   0.626     .8163521    1.129864
-----------------+------------------------------------------------------------
         /cut1 |   -1.22569   .5121845                      -2.229553    -.221827
         /cut2 |   .4680011    .508652                      -.5289385    1.464941
         /cut3 |   1.729567   .5177846                       .7147281    2.744407
         /cut4 |   3.216939    .558594                       2.122115    4.311763
------------------------------------------------------------------------------

. ologit LocalAccess_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -423.57394
Iteration 1:   log likelihood = -418.37949
Iteration 2:   log likelihood = -418.36755
Iteration 3:   log likelihood = -418.36754

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      10.41
                                                Prob > chi2     =     0.0340
Log likelihood = -418.36754                     Pseudo R2       =     0.0123

------------------------------------------------------------------------------
LocalAccess_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
   Income_n |   .9988302   .0516976    -0.02   0.982     .9024747    1.105473
     Age_n |   1.139624   .0863146     1.73   0.084     .9824084       1.322
    Educ_n |   .9789264    .065476    -0.32   0.750     .8586517    1.116049
HouseSize_n |   .8362725   .0740421    -2.02   0.043     .7030463    .9947449
-------------+----------------------------------------------------------------
      /cut1 |  -1.263495   .5111987                      -2.265426   -.2615645
      /cut2 |   .1329882   .5063603                      -.8594597    1.125436
      /cut3 |    1.4773   .5117484                       .4742918    2.480309
      /cut4 |   3.501542   .6030038                       2.319676    4.683408
------------------------------------------------------------------------------

. ologit MeadLocalAvail_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -430.93302
Iteration 1:   log likelihood = -422.23086
Iteration 2:   log likelihood = -422.20118
Iteration 3:   log likelihood = -422.20118

Ordered logistic regression                     Number of obs   =        293
                                                LR chi2(4)      =      17.46
                                                Prob > chi2     =     0.0016
Log likelihood = -422.20118                     Pseudo R2       =     0.0203

------------------------------------------------------------------------------
MeadLocalAvail_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
      Income_n |   1.033232   .0535889     0.63   0.528     .9333615    1.143788
        Age_n |   .7786418   .0617204    -3.16   0.002     .6666007    .9095146
       Educ_n |   .9950224     .06679    -0.07   0.941      .872362     1.13493
   HouseSize_n |   1.143983    .097021     1.59   0.113     .9687896    1.350859
-----------------+------------------------------------------------------------
        /cut1 |  -2.835941   .5596925                      -3.932919   -1.738964
        /cut2 |  -.7324512   .5281507                      -1.767608    .3027052
        /cut3 |   .2107342   .5263856                      -.8209627    1.242431
        /cut4 |   2.106219   .5502301                       1.027787     3.18465
------------------------------------------------------------------------------

. ologit LocalExpense_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -380.97902
Iteration 1:   log likelihood = -377.24524
Iteration 2:   log likelihood = -377.23813
Iteration 3:   log likelihood = -377.23813
```

```
Ordered logistic regression                     Number of obs   =        293
                                                LR chi2(4)      =       7.48
                                                Prob > chi2     =     0.1125
Log likelihood = -377.23813                     Pseudo R2       =     0.0098

------------------------------------------------------------------------------
LocalExpense_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
     Income_n |   1.036753   .0541271     0.69   0.489     .9359135    1.148458
       Age_n |     1.2038    .093392     2.39   0.017     1.033992    1.401494
      Educ_n |   1.014582   .0702432     0.21   0.834     .8858399    1.162034
  HouseSize_n |    .994643   .0851826    -0.06   0.950      .840948    1.176428
---------------+--------------------------------------------------------------
       /cut1 |   -.179462   .5069189                     -1.173005    .8140808
       /cut2 |   1.606831   .5170893                      .5933547    2.620308
       /cut3 |    3.46105   .5535479                      2.376116    4.545983
       /cut4 |   5.279607   .7161217                      3.876035     6.68318
------------------------------------------------------------------------------

. ologit LocalQuality_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood =  -322.7493
Iteration 1:   log likelihood = -316.96531
Iteration 2:   log likelihood = -316.95224
Iteration 3:   log likelihood = -316.95223

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      11.59
                                                Prob > chi2     =     0.0206
Log likelihood = -316.95223                     Pseudo R2       =     0.0180

------------------------------------------------------------------------------
LocalQuality_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
     Income_n |    1.17125   .0643969     2.88   0.004     1.051597    1.304517
       Age_n |   .9906072   .0807279    -0.12   0.908     .8443727    1.162168
      Educ_n |   .9856239   .0690325    -0.21   0.836     .8591986    1.130652
  HouseSize_n |    .846278   .0769621    -1.84   0.066      .708114      1.0114
---------------+--------------------------------------------------------------
       /cut1 |   .0791648   .5457417                     -.9904693    1.148799
       /cut2 |   2.134307   .5640504                      1.028789    3.239825
       /cut3 |   3.850785   .6371095                      2.602074    5.099497
       /cut4 |   6.075016   1.137726                      3.845115    8.304917
```

Question 2 Regressions:

. ologit Price_n Income_n Age_n Educ_n HouseSize_n, or

```
Iteration 0:   log likelihood = -351.52631
Iteration 1:   log likelihood = -332.54025
Iteration 2:   log likelihood = -332.37239
Iteration 3:   log likelihood = -332.37219
Iteration 4:   log likelihood = -332.37219

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      38.31
                                                Prob > chi2     =     0.0000
Log likelihood = -332.37219                     Pseudo R2       =     0.0545

------------------------------------------------------------------------------
    Price_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.287339   .0750936     4.33   0.000      1.14826    1.443263
      Age_n |   1.159783   .0968731     1.77   0.076     .9846428    1.366077
     Educ_n |   1.091513   .0799382     1.20   0.232     .9455627    1.259992
 HouseSize_n |   .9538434   .0832048    -0.54   0.588     .8039441    1.131692
------------+-----------------------------------------------------------------
       /cut1 |   2.065865   .5627799                      .9628362    3.168893
       /cut2 |   4.018425   .5981754                      2.846023    5.190828
       /cut3 |    4.6912   .6131417                      3.489464    5.892936
       /cut4 |   6.572189   .7405512                      5.120735    8.023643
------------------------------------------------------------------------------
```

. ologit Quality_n Income_n Age_n Educ_n HouseSize_n, or

```
Iteration 0:   log likelihood = -236.09302
Iteration 1:   log likelihood = -234.11067
Iteration 2:   log likelihood = -234.10964
Iteration 3:   log likelihood = -234.10964

Ordered logistic regression                     Number of obs   =        289
                                                LR chi2(4)      =       3.97
                                                Prob > chi2     =     0.4105
Log likelihood = -234.10964                     Pseudo R2       =     0.0084

------------------------------------------------------------------------------
```

```
  Quality_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+----------------------------------------------------------------
   Income_n |   .9959634   .0577266    -0.07   0.944     .8890112    1.115782
     Age_n |   .8792078   .0746517    -1.52   0.129     .7444197    1.038401
    Educ_n |   1.092829   .0823666     1.18   0.239     .9427515    1.266798
HouseSize_n |   .9843702   .0901424    -0.17   0.863     .8226418    1.177894
------------+----------------------------------------------------------------
      /cut1 |  -.0360956   .5623753                     -1.138331     1.06614
      /cut2 |   3.309982   .6422512                      2.051193    4.568771
      /cut3 |   5.540433   1.139308                      3.307431    7.773436
------------------------------------------------------------------------------

. ologit Variety_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -337.12417
Iteration 1:   log likelihood = -330.99212
Iteration 2:   log likelihood = -330.96611
Iteration 3:   log likelihood =  -330.9661

Ordered logistic regression                     Number of obs   =        292
                                  LR chi2(4)      =      12.32
                                  Prob > chi2     =     0.0151
Log likelihood =  -330.9661                     Pseudo R2       =     0.0183

------------------------------------------------------------------------------
  Variety_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+----------------------------------------------------------------
   Income_n |   1.006933   .0555619     0.13   0.900     .9037158    1.121939
     Age_n |      .7969   .0652201    -2.77   0.006     .6787965    .9355524
    Educ_n |   1.121499   .0806184     1.60   0.111     .9741156     1.29118
HouseSize_n |   1.032412   .0872336     0.38   0.706     .8748446    1.218359
------------+----------------------------------------------------------------
      /cut1 |  -1.000526   .5325473                     -2.044299    .0432477
      /cut2 |   1.190443   .5343304                      .1431746    2.237711
      /cut3 |   2.862284   .5755922                      1.734144    3.990425
------------------------------------------------------------------------------

. ologit StoreFam_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -379.80543
Iteration 1:   log likelihood = -378.96963
Iteration 2:   log likelihood = -378.96933
Iteration 3:   log likelihood = -378.96933
```

```
Ordered logistic regression                     Number of obs   =        293
                                                LR chi2(4)      =       1.67
                                                Prob > chi2     =     0.7958
Log likelihood = -378.96933                     Pseudo R2       =     0.0022

------------------------------------------------------------------------------
 StoreFam_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   .9609665   .0500644    -0.76   0.445     .8676856    1.064276
    Age_n |   .9972212    .076664    -0.04   0.971      .857735    1.159391
   Educ_n |   1.080905   .0754348     1.11   0.265     .9427216    1.239344
HouseSize_n |   1.057765   .0866552     0.69   0.493      .900858    1.242002
------------+-----------------------------------------------------------------
      /cut1 |    -.48626    .521156                     -1.507707    .5351869
      /cut2 |   1.117798   .5275624                      .0837951    2.151802
      /cut3 |   2.960397   .5653776                      1.852278    4.068517
      /cut4 |   3.634108   .6044563                      2.449395     4.81882
------------------------------------------------------------------------------

. ologit SnapWic_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood =  -281.6102
Iteration 1:   log likelihood = -248.90307
Iteration 2:   log likelihood = -246.69734
Iteration 3:   log likelihood = -246.69129
Iteration 4:   log likelihood = -246.69129

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      69.84
                                                Prob > chi2     =     0.0000
Log likelihood = -246.69129                     Pseudo R2       =     0.1240

------------------------------------------------------------------------------
  SnapWic_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.470005   .1030566     5.50   0.000     1.281281    1.686528
    Age_n |   1.208787    .111629     2.05   0.040     1.008656    1.448627
   Educ_n |   1.230774   .1070687     2.39   0.017     1.037839    1.459577
HouseSize_n |   .8104827   .0783936    -2.17   0.030     .6705199    .9796611
------------+-----------------------------------------------------------------
      /cut1 |   .1972904   .5967169                     -.9722532    1.366834
      /cut2 |   .8978349   .5984165                     -.2750398     2.07071
      /cut3 |   2.012348   .6134157                      .8100756    3.214621
      /cut4 |   2.177814   .6148803                      .9726705    3.382957
```

```
------------------------------------------------------------------------------

. ologit Conv_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -376.77569
Iteration 1:   log likelihood = -372.31423
Iteration 2:   log likelihood = -372.29786
Iteration 3:   log likelihood = -372.29785

Ordered logistic regression                     Number of obs   =        295
                                  LR chi2(4)      =       8.96
                                  Prob > chi2     =     0.0622
Log likelihood = -372.29785                     Pseudo R2       =     0.0119

------------------------------------------------------------------------------
     Conv_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.088273   .0573383     1.61   0.108     .9814998    1.206661
      Age_n |   .8648593   .0678915    -1.85   0.064     .7415255    1.008707
     Educ_n |    1.04545   .0725646     0.64   0.522     .9124763    1.197803
 HouseSize_n |   .8532919   .0712169    -1.90   0.057     .7245281     1.00494
------------+-----------------------------------------------------------------
      /cut1 |  -1.465216    .523614                     -2.491481   -.4389517
      /cut2 |   .7108704   .5157482                     -.2999776    1.721718
      /cut3 |   1.832682   .5289878                      .7958846    2.869479
      /cut4 |   3.792154   .6692411                      2.480466    5.103843
------------------------------------------------------------------------------

. ologit TravelConv_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -399.05255
Iteration 1:   log likelihood =  -390.6646
Iteration 2:   log likelihood = -390.62473
Iteration 3:   log likelihood = -390.62472

Ordered logistic regression                     Number of obs   =        292
                                  LR chi2(4)      =      16.86
                                  Prob > chi2     =     0.0021
Log likelihood = -390.62472                     Pseudo R2       =     0.0211

------------------------------------------------------------------------------
TravelConv_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.144185   .0613993     2.51   0.012     1.029957    1.271082
```

```
      Age_n |   .7789328   .0602316    -3.23   0.001     .6693914    .9063998
     Educ_n |   1.006474   .0704631     0.09   0.927     .8774256    1.154503
 HouseSize_n |   .8850973   .0714742    -1.51   0.131      .755534    1.036879
-------------+----------------------------------------------------------------
      /cut1 |  -1.929125   .5081377                     -2.925057   -.9331933
      /cut2 |  -.0746727    .496032                     -1.046878    .8975322
      /cut3 |   1.637335   .5078786                      .6419112    2.632759
      /cut4 |   2.832716   .5631817                        1.7289    3.936532
------------------------------------------------------------------------------

. ologit LocalFoodAvail_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -434.59796
Iteration 1:   log likelihood = -424.86046
Iteration 2:   log likelihood = -424.81276
Iteration 3:   log likelihood = -424.81275

Ordered logistic regression                     Number of obs   =        295
                                                LR chi2(4)      =      19.57
                                                Prob > chi2     =     0.0006
Log likelihood = -424.81275                     Pseudo R2       =     0.0225

------------------------------------------------------------------------------
LocalFoodAvail_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
       Income_n |   1.159051   .0591981     2.89   0.004     1.048644    1.281084
         Age_n |   .8200393   .0631502    -2.58   0.010     .7051552    .9536403
        Educ_n |   1.062435   .0729068     0.88   0.377     .9287331    1.215385
    HouseSize_n |   .9603994   .0796281    -0.49   0.626     .8163521    1.129864
-----------------+------------------------------------------------------------
         /cut1 |   -1.22569   .5121845                     -2.229553    -.221827
         /cut2 |   .4680011    .508652                     -.5289385    1.464941
         /cut3 |   1.729567   .5177846                      .7147281    2.744407
         /cut4 |   3.216939    .558594                      2.122115    4.311763
------------------------------------------------------------------------------

. ologit OrganAvail_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -428.83464
Iteration 1:   log likelihood = -425.88837
Iteration 2:   log likelihood = -425.88488
Iteration 3:   log likelihood = -425.88488

Ordered logistic regression                     Number of obs   =        294
```

```
                                  LR chi2(4)      =       5.90
                                  Prob > chi2     =     0.2068
Log likelihood = -425.88488                       Pseudo R2       =     0.0069

------------------------------------------------------------------------------
OrganAvail_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Income_n |   .9643455   .0516082    -0.68   0.498     .8683194    1.070991
     Age_n |   1.054962   .0809972     0.70   0.486      .907578    1.226281
    Educ_n |   1.010044   .0696049     0.15   0.885     .8824329    1.156109
HouseSize_n |   1.228525   .1058366     2.39   0.017     1.037656    1.454502
-------------+----------------------------------------------------------------
      /cut1 |  -1.756743   .5284623                      -2.79251   -.7209758
      /cut2 |  -.8404583   .5110565                     -1.842111    .161194
      /cut3 |   .5956848    .508627                     -.4012059    1.592575
      /cut4 |   1.231351   .5114668                      .2288942    2.233807
------------------------------------------------------------------------------

. ologit OtherStuff_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -451.09298
Iteration 1:   log likelihood =  -449.0496
Iteration 2:   log likelihood =  -449.0481
Iteration 3:   log likelihood =  -449.0481

Ordered logistic regression                       Number of obs   =        293
                                  LR chi2(4)      =       4.09
                                  Prob > chi2     =     0.3940
Log likelihood =  -449.0481                       Pseudo R2       =     0.0045

------------------------------------------------------------------------------
OtherStuff_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Income_n |   1.006259   .0539178     0.12   0.907     .9059422    1.117685
     Age_n |    1.08585   .0814709     1.10   0.272     .9373556    1.257868
    Educ_n |   1.082008   .0747369     1.14   0.254     .9450088    1.238868
HouseSize_n |   .9469873   .0769421    -0.67   0.503     .8075782    1.110462
-------------+----------------------------------------------------------------
      /cut1 |  -.5654345   .4919901                     -1.529717    .3988483
      /cut2 |   .6389312   .4916519                     -.3246887    1.602551
      /cut3 |   1.665091   .4979905                      .6890472    2.641134
      /cut4 |   3.032506   .5280428                      1.997561    4.067451
------------------------------------------------------------------------------
```

```
. ologit Friend_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood =  -364.5336
Iteration 1:   log likelihood = -359.61768
Iteration 2:   log likelihood = -359.60754
Iteration 3:   log likelihood = -359.60754

Ordered logistic regression                     Number of obs   =        295
                                                LR chi2(4)      =       9.85
                                                Prob > chi2     =     0.0430
Log likelihood = -359.60754                     Pseudo R2       =     0.0135

------------------------------------------------------------------------------
   Friend_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.032213   .0550957     0.59   0.553     .9296841    1.146049
     Age_n |    .966768   .0760139    -0.43   0.667     .8286956    1.127845
    Educ_n |   1.184191   .0834603     2.40   0.016     1.031407    1.359607
 HouseSize_n |   1.032018   .0899444     0.36   0.718     .8699645    1.224257
------------+-----------------------------------------------------------------
      /cut1 |  -2.287675   .5840282                     -3.432349     -1.143
      /cut2 |  -1.214841    .542375                     -2.277876   -.1518051
      /cut3 |   1.121067   .5326156                      .0771598    2.164975
      /cut4 |   1.433518   .5340454                      .3868086    2.480228
------------------------------------------------------------------------------

. ologit Animal_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -462.03056
Iteration 1:   log likelihood = -453.69346
Iteration 2:   log likelihood = -453.66041
Iteration 3:   log likelihood = -453.66041

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      16.74
                                                Prob > chi2     =     0.0022
Log likelihood = -453.66041                     Pseudo R2       =     0.0181

------------------------------------------------------------------------------
   Animal_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.123222   .0575578     2.27   0.023     1.015891    1.241893
     Age_n |   1.210835   .0932898     2.48   0.013     1.041127    1.408207
    Educ_n |   1.034745   .0697672     0.51   0.612     .9066533    1.180932
```

```
 HouseSize_n |   1.076049   .0859464     0.92   0.359     .9201202    1.258402
-------------+----------------------------------------------------------------
       /cut1 |  -.3050571   .4979898                     -1.281099    .6709849
       /cut2 |    1.28555   .4967178                      .3120014    2.259099
       /cut3 |   2.376674   .5108312                      1.375463    3.377885
       /cut4 |    3.32303   .5274478                      2.289251    4.356809
------------------------------------------------------------------------------

. ologit EnvEffect_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -453.71314
Iteration 1:   log likelihood =  -443.3257
Iteration 2:   log likelihood =  -443.2774
Iteration 3:   log likelihood = -443.27738

Ordered logistic regression                     Number of obs   =        293
                                  LR chi2(4)      =      20.87
                                  Prob > chi2     =     0.0003
Log likelihood = -443.27738                     Pseudo R2       =     0.0230

------------------------------------------------------------------------------
 EnvEffect_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Income_n |   1.231294   .0641208     4.00   0.000     1.111821    1.363606
       Age_n |   .9988644   .0769813    -0.01   0.988     .8588264    1.161736
      Educ_n |   .9778356   .0671847    -0.33   0.744     .8546374    1.118793
 HouseSize_n |   1.016692   .0812178     0.21   0.836     .8693446    1.189015
-------------+----------------------------------------------------------------
       /cut1 |   -.833294   .5020448                     -1.817284    .1506956
       /cut2 |   .7767037   .4971768                      -.1977449    1.751152
       /cut3 |    2.04327   .5084512                      1.046724    3.039816
       /cut4 |   3.072171   .5251905                      2.042816    4.101525
------------------------------------------------------------------------------

. ologit WPEO Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood =  -449.3195
Iteration 1:   log likelihood = -441.28802
Iteration 2:   log likelihood = -441.25729
Iteration 3:   log likelihood = -441.25729

Ordered logistic regression                     Number of obs   =        291
                                  LR chi2(4)      =      16.12
                                  Prob > chi2     =     0.0029
```

```
Log likelihood = -441.25729                     Pseudo R2       =     0.0179

------------------------------------------------------------------------------
     WPEO_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.152592   .0595763     2.75   0.006     1.041544    1.275479
      Age_n |   .9298278   .0707734    -0.96   0.339     .8009654    1.079422
     Educ_n |   1.033923   .0703355     0.49   0.624     .9048628     1.18139
 HouseSize_n |   1.104263   .0927254     1.18   0.238     .9366921    1.301812
------------+-----------------------------------------------------------------
      /cut1 |  -.7884669   .5117298                     -1.791439    .2145052
      /cut2 |   .6475212   .5064328                     -.3450688    1.640111
      /cut3 |   1.888883   .5189774                      .8717064     2.90606
      /cut4 |   3.311244   .5492278                      2.234777     4.38771
------------------------------------------------------------------------------

. ologit LocalNWPA_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood =  -454.2238
Iteration 1:   log likelihood = -444.88534
Iteration 2:   log likelihood = -444.84572
Iteration 3:   log likelihood = -444.84571

Ordered logistic regression                     Number of obs   =        292
                                  LR chi2(4)      =      18.76
                                  Prob > chi2     =     0.0009
Log likelihood = -444.84571                     Pseudo R2       =     0.0206

------------------------------------------------------------------------------
 LocalNWPA_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Income_n |   1.161546   .0597975     2.91   0.004     1.050064    1.284864
      Age_n |   .9030675   .0680054    -1.35   0.176     .7791491    1.046694
     Educ_n |   1.040378   .0698452     0.59   0.555     .9121076    1.186686
 HouseSize_n |   1.106288   .0931071     1.20   0.230     .9380575    1.304688
-------------+----------------------------------------------------------------
      /cut1 |  -.7501585   .5073101                     -1.744468     .244151
      /cut2 |   .5108024   .5035168                     -.4760724    1.497677
      /cut3 |   1.722887    .514597                      .7142956    2.731479
      /cut4 |   3.254472   .5449509                      2.186388    4.322556
------------------------------------------------------------------------------

. ologit Within50_n Income_n Age_n Educ_n HouseSize_n, or
```

```
Iteration 0:   log likelihood =  -449.8341
Iteration 1:   log likelihood = -441.23296
Iteration 2:   log likelihood = -441.19694
Iteration 3:   log likelihood = -441.19694

Ordered logistic regression                     Number of obs   =        292
                                                LR chi2(4)      =      17.27
                                                Prob > chi2     =     0.0017
Log likelihood = -441.19694                     Pseudo R2       =     0.0192

------------------------------------------------------------------------------
  Within50_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Income_n |   1.179723   .0612764     3.18   0.001     1.065534    1.306148
       Age_n |   .8811592   .0681406    -1.64   0.102     .7572345    1.025365
      Educ_n |   1.004446   .0678165     0.07   0.948     .8799469    1.146559
 HouseSize_n |   1.043784   .0851018     0.53   0.599     .8896318    1.224646
-------------+----------------------------------------------------------------
       /cut1 |  -1.538746   .5223068                     -2.562448   -.5150433
       /cut2 |  -.0083169    .508403                     -1.004769    .9881347
       /cut3 |   1.343263   .5176464                      .3286948    2.357831
       /cut4 |   2.607583   .5364258                      1.556207    3.658958
------------------------------------------------------------------------------

. ologit Within100_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -446.30354
Iteration 1:   log likelihood = -437.66069
Iteration 2:   log likelihood = -437.62517
Iteration 3:   log likelihood = -437.62516

Ordered logistic regression                     Number of obs   =        292
                                                LR chi2(4)      =      17.36
                                                Prob > chi2     =     0.0016
Log likelihood = -437.62516                     Pseudo R2       =     0.0194

------------------------------------------------------------------------------
 Within100_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Income_n |    1.17363   .0612421     3.07   0.002     1.059532    1.300015
       Age_n |   .8823548   .0678764    -1.63   0.104      .758863    1.025943
      Educ_n |    1.01429   .0685941     0.21   0.834     .8883767    1.158049
 HouseSize_n |   1.051781   .0847234     0.63   0.531     .8981706    1.231662
-------------+----------------------------------------------------------------
```

```
       /cut1 |  -1.456857   .5165309                -2.469239    -.444475
       /cut2 |   .0391911   .5048213                -.9502404    1.028623
       /cut3 |   1.415404   .5130119                 .4099189    2.420889
       /cut4 |   2.843094    .535073                 1.79437    3.891818
------------------------------------------------------------------------------

. ologit ProdUS_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -403.57971
Iteration 1:   log likelihood =  -394.1178
Iteration 2:   log likelihood =  -394.0823
Iteration 3:   log likelihood = -394.08229

Ordered logistic regression                     Number of obs   =        293
                                                LR chi2(4)      =      18.99
                                                Prob > chi2     =     0.0008
Log likelihood = -394.08229                     Pseudo R2       =     0.0235

------------------------------------------------------------------------------
   ProdUS_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.001249   .0521804     0.02   0.981     .9040273    1.108927
     Age_n |   .7893804   .0606316    -3.08   0.002     .6790571    .9176275
    Educ_n |    1.13876   .0790814     1.87   0.061      .993849    1.304801
 HouseSize_n |    1.14423   .0922641     1.67   0.095     .9769616    1.340138
------------+-----------------------------------------------------------------
       /cut1 |  -.5929941   .4999498               -1.572878    .3868895
       /cut2 |   1.070498   .5020551                .0864884    2.054508
       /cut3 |   1.976738   .5134575                  .97038    2.983096
       /cut4 |   3.352579   .5692626                2.236845    4.468313
------------------------------------------------------------------------------
```

Question 3 Regressions

```
. ologit EnvCare_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -263.47317
Iteration 1:   log likelihood = -260.62909
Iteration 2:   log likelihood = -260.62481
Iteration 3:   log likelihood = -260.62481

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =       5.70
```

```
                                    Prob > chi2     =     0.2230
Log likelihood = -260.62481                     Pseudo R2       =     0.0108

------------------------------------------------------------------------------
  EnvCare_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.126059   .0647437     2.06   0.039     1.006053    1.260381
     Age_n |   .9340593   .0795168    -0.80   0.423     .7905172    1.103666
    Educ_n |    .982934   .0735418    -0.23   0.818      .848865    1.138178
HouseSize_n |   .9995488   .0914863    -0.00   0.996      .835402    1.195948
------------+-----------------------------------------------------------------
      /cut1 |   .6698005   .5642128                     -.4360363    1.775637
      /cut2 |   3.052247   .6044918                      1.867465    4.237029
      /cut3 |   4.958876   .8045408                      3.382005    6.535747
      /cut4 |   6.065706   1.146503                      3.818601    8.312811
------------------------------------------------------------------------------

. ologit ClimChng_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -393.97886
Iteration 1:   log likelihood = -390.78597
Iteration 2:   log likelihood = -390.78256
Iteration 3:   log likelihood = -390.78256

Ordered logistic regression                     Number of obs   =        294
                                    LR chi2(4)      =       6.39
                                    Prob > chi2     =     0.1717
Log likelihood = -390.78256                     Pseudo R2       =     0.0081

------------------------------------------------------------------------------
  ClimChng_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.105917   .0572281     1.95   0.052     .9992524    1.223967
     Age_n |   1.111481   .0874338     1.34   0.179     .9526709    1.296764
    Educ_n |   .9739551   .0657986    -0.39   0.696     .8531656    1.111846
HouseSize_n |   .9943448    .082655    -0.07   0.946     .8448524    1.170289
------------+-----------------------------------------------------------------
      /cut1 |   .6409264   .5163061                     -.371015    1.652868
      /cut2 |   1.759939   .5233316                      .7342277     2.78565
      /cut3 |   2.933847   .5429394                      1.869705    3.997988
      /cut4 |   3.661894   .5704433                      2.543845    4.779942
------------------------------------------------------------------------------

. ologit LocalEcon_n Income_n Age_n Educ_n HouseSize_n, or
```

```
Iteration 0:   log likelihood = -221.16063
Iteration 1:   log likelihood = -218.07095
Iteration 2:   log likelihood = -218.05466
Iteration 3:   log likelihood = -218.05466

Ordered logistic regression                     Number of obs   =        295
                                                LR chi2(4)      =       6.21
                                                Prob > chi2     =     0.1839
Log likelihood = -218.05466                     Pseudo R2       =     0.0140

------------------------------------------------------------------------------
 LocalEcon_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Income_n |   1.005278   .0618837     0.09   0.932     .8910197    1.134188
       Age_n |   .8172749   .0749865    -2.20   0.028     .6827612    .9782898
      Educ_n |   1.054489    .085798     0.65   0.514     .8990512      1.2368
 HouseSize_n |   .8647873   .0887818    -1.42   0.157     .7071675    1.057539
-------------+----------------------------------------------------------------
       /cut1 |  -.0659096   .5974034                     -1.236799    1.104979
       /cut2 |   2.198953   .6412442                      .9421371    3.455768
       /cut3 |   4.815282   1.152999                      2.555445    7.075119
------------------------------------------------------------------------------

. ologit PayMore_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -338.50275
Iteration 1:   log likelihood = -337.01254
Iteration 2:   log likelihood = -337.01137
Iteration 3:   log likelihood = -337.01137

Ordered logistic regression                     Number of obs   =        295
                                                LR chi2(4)      =       2.98
                                                Prob > chi2     =     0.5607
Log likelihood = -337.01137                     Pseudo R2       =     0.0044

------------------------------------------------------------------------------
   PayMore_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    Income_n |   .9680367   .0515999    -0.61   0.542     .8720063    1.074642
       Age_n |   .9289571   .0755547    -0.91   0.365     .7920726    1.089498
      Educ_n |   .9476794   .0661087    -0.77   0.441     .8265762    1.086526
 HouseSize_n |   1.037722   .0866372     0.44   0.657     .8810815    1.222211
-------------+----------------------------------------------------------------
```

```
       /cut1 |  -1.050526   .5422719                -2.113359    .0123075
       /cut2 |   1.113831   .5448409                 .0459623    2.181699
       /cut3 |   2.265859   .5756296                 1.137645    3.394072
       /cut4 |   3.285209   .6579981                 1.995557    4.574862
------------------------------------------------------------------------------

. ologit KWFCF_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -362.07287
Iteration 1:   log likelihood = -352.86168
Iteration 2:   log likelihood = -352.82175
Iteration 3:   log likelihood = -352.82174

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      18.50
                                                Prob > chi2     =     0.0010
Log likelihood = -352.82174                     Pseudo R2       =     0.0256

------------------------------------------------------------------------------
    KWFCF_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.185058   .0625507     3.22   0.001     1.068589    1.314221
     Age_n |   .8717851   .0691001    -1.73   0.083     .7463472    1.018305
    Educ_n |   1.021165   .0704848     0.30   0.762     .8919546    1.169093
HouseSize_n |   1.041816   .0875647     0.49   0.626     .8835832    1.228385
------------+-----------------------------------------------------------------
       /cut1 |  -.1262179   .5161004               -1.137756    .8853203
       /cut2 |   1.632546   .5282665                .5971621    2.667929
       /cut3 |   3.848385   .5888866                2.694189    5.002582
       /cut4 |   5.766676   .8764197                4.048925    7.484427
------------------------------------------------------------------------------

. ologit MeadCom_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -421.18822
Iteration 1:   log likelihood = -415.97792
Iteration 2:   log likelihood = -415.96495
Iteration 3:   log likelihood = -415.96495

Ordered logistic regression                     Number of obs   =        294
                                                LR chi2(4)      =      10.45
                                                Prob > chi2     =     0.0335
Log likelihood = -415.96495                     Pseudo R2       =     0.0124
```

```
------------------------------------------------------------------------------
  MeadCom_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.041685   .0523453     0.81   0.416     .9439804    1.149502
     Age_n |   1.017247   .0782405     0.22   0.824     .8748973    1.182758
    Educ_n |   .8073657   .0551394    -3.13   0.002     .7062152    .9230039
HouseSize_n |   .9930993   .0805732    -0.09   0.932     .8470949    1.164269
------------+-----------------------------------------------------------------
      /cut1 |  -2.129191    .526178                     -3.160481   -1.097901
      /cut2 |  -.5164872   .5125961                     -1.521157    .4881828
      /cut3 |   1.085768   .5187624                      .0690123    2.102524
      /cut4 |   1.602767   .5292935                      .5653712    2.640163
------------------------------------------------------------------------------

. ologit ComunInv_n Income_n Age_n Educ_n HouseSize_n, or

Iteration 0:   log likelihood = -396.38447
Iteration 1:   log likelihood = -389.39638
Iteration 2:   log likelihood = -389.36837
Iteration 3:   log likelihood = -389.36836

Ordered logistic regression                     Number of obs   =        295
                                  LR chi2(4)      =      14.03
                                  Prob > chi2     =     0.0072
Log likelihood = -389.36836                     Pseudo R2       =     0.0177

------------------------------------------------------------------------------
 ComunInv_n | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------+-----------------------------------------------------------------
   Income_n |   1.035094    .053566     0.67   0.505     .9352557    1.145591
     Age_n |   1.004285   .0773968     0.06   0.956     .8634906    1.168035
    Educ_n |   .7805801    .054249    -3.56   0.000     .6811776    .8944881
HouseSize_n |   1.029984   .0826117     0.37   0.713     .8801538    1.205321
------------+-----------------------------------------------------------------
      /cut1 |  -2.058537   .5251826                     -3.087876   -1.029198
      /cut2 |  -.1908905   .5136658                     -1.197657     .815876
      /cut3 |   1.489353   .5310852                      .4484455    2.530261
      /cut4 |   2.236973   .5602078                      1.138986     3.33496
------------------------------------------------------------------------------
```