

Closing the Food Access Gap in American Underserved Communities

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By

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**ABSTRACT**

Malnutrition is a global issue that affects millions of people across the world. Malnutrition is not just the lack of food, but also consists of the overabundance of unhealthy food due to a lack of healthy food. This instance of malnutrition is particularly troublesome for cities in the United States. In the U.S., there are many people who simply do not have access to healthy food options. Many of these individuals live in “food-deserts” or areas where no grocery stores that sell fresh produce exist within a 1-mile radius. In low-income areas where many people do not have access to a car, residents of food-deserts may have no way of accessing healthy food options. One way to combat the problem of food-deserts is to supply these areas with healthy food options. This research is centered on answering two research questions: 1) What food supply chain model (grocery delivery, rideshare, veggie-box) would residents of low-income areas prefer? 2) What is the feasibility of implementing this food supply chain model to increase healthy foods in low-income areas? This research was conducted by surveying residents of Somerville, MA, and also interviewing stakeholders within the potential supply chain for sourcing food-desert neighborhoods with fresh produce. These data were analyzed using a series of logistic regressions, which resulted in 82.7%, 75.2%, and 89.5% prediction power for the rideshare, grocery delivery, and veggie box supply chain models, respectively. The research shows that residents preferred the veggie-box model and that this model was also feasible in supplying neighborhood markets within food-deserts with fresh produce.

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**Jamal Taylor, MIT SCM Class of 2020**

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**Luiz Barreto, MIT SCM Class of 2020**

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## 1. INTRODUCTION

Malnutrition is a global problem that affects an estimated three billion people (FAO, 2016). Often, when people think about malnutrition they only consider individuals who do not consume enough food. However, malnutrition includes those who overconsume unhealthy foods as well. This side of malnutrition is particularly prevalent in populations across the world who do not have sufficient access to healthy food options. The United States is no exception, with 23.5 million residents living in food-deserts. A “food-desert” is a neighborhood located further than one mile away from a grocery store that sells fresh fruits and vegetables. Living in a food-desert is strongly correlated with malnutrition and diet-related health risks and diseases.

These adverse effects are compounded when the food-desert is also a low-income community. When this is the case, residents might not have access to reliable transportation and will therefore do the majority of their grocery shopping at local neighborhood markets with limited ability to source fresh produce. Without a car, this could mean the inconvenience of carrying groceries on a crowded bus or train, or the added expense of a taxi or rideshare service like Uber or Lyft. Alternatively, customers might opt into delivery services such as Instacart, Amazon Fresh, or Walmart Delivery service. However, each of these services come with an additional delivery fee that might be impractical for an already price-sensitive population. This research project will show that neighborhood markets are well positioned to meet the needs of underserved American communities by sourcing them with fresh produce.

This project will answer two main research questions:

1. Which food supply chain (grocery delivery, rideshare, veggie-box) model will residents of low-income areas prefer?



2. What is the feasibility of this food supply chain to increase healthy foods in low-income areas?

Neighborhood markets seem to be well positioned to fulfill the need for fresh produce in their communities. The stores' close proximity to their customer base is a strategic advantage over other means for consumers to get fruits and vegetables. Also, since many individuals in this demographic already purchase their groceries at convenience stores, sourcing these neighborhood markets with fresh produce allows customers to maintain their same shopping habits. Otherwise, customers might have to travel outside of their neighborhood to purchase fresh produce. From this research, it was found that 51.5% of those asked indicated that they shop at neighborhood markets at least once per month. Moreover, 34.2% of respondents shop at neighborhood markets frequently (2 – 3 times per month or more).

While neighborhood markets do have a competitive advantage due to their location, they still may have difficulty providing fresh produce for three main reasons. First, because these stores are very localized and serve a relatively small market, they might have difficulty purchasing fresh produce from typical suppliers (e.g., local farms) that have minimum order quantities that are much higher than local demand. Second, produce tends to have a relatively short shelf-life. Since the viability of these stores depends on slim profit margins, sourcing fresh produce that may expire before a customer's purchase might not be worth the risk. Lastly, customer preference plays a role. Customers have historically bought certain (usually unhealthy) foods. Therefore, owners (often incorrectly) assume these are the only products their consumers want to purchase. This makes them skeptical that their customers will purchase fresh produce, even if it is offered. Again, due to tight profit margins, owners might prefer to continue selling goods that have historically sold best.

Despite these drawbacks, neighborhood markets have become an important part of millions of people's shopping habits. Therefore, it is imperative to analyze the viability of utilizing these markets to expand health food options to under resourced communities that have historically been without.

This research is focused on the Somerville community, a Massachusetts suburb outside of Boston. In order to correctly frame this research, it is important to analyze the correlation between food-deserts and community health. Chen, Jaenicke, and Volpe (2016) studied over 38,651 individuals and 18,381 households in the U.S. to understand the associations between obesity and living in a food-desert. Their research identified a positive correlation between food-desert status and obesity at the neighborhood level. In a separate study, Somerville's city government invested in an extensive research report, *Community Food System Assessment* (2018). This report outlined low-income areas, areas with a high population of racial and ethnic minorities, and areas in the city where English is not the most common language. This report then measured the distance from those areas to each food access point in the city. This project showed that, across the city, the majority of areas where Somerville residents had to walk more than 10 minutes to get to a full-service grocery store were areas where low-income residents were located.

Both of the aforementioned studies analyzed the problem of food-deserts from different perspectives. However, neither of these studies assessed the feasibility of using neighborhood markets, or "nanostores," (Fransoo, Blanco, Mejia-Argueta, 2017) as a means to bring fresh produce closer to low-income communities in Somerville. This research will fill this gap by collecting primary data from surveys and interviews, assess consumer preferences in Somerville, and consult secondary data to verify the feasibility of nanostore supply chains that will promote healthy food access.

To answer the first research question, 17 interviews were conducted for each tier of the supply chain. The study sample of the interviews included wholesalers, farmers, farmer associations, and nanostores. Each interview consisted of four – six open-ended questions which aim not only at outlining the behaviors within each tier of the healthy food retail supply chain, but also how transactions between each tier occur. These questions helped identify key performance metrics which were used to assess the performance of the food supply chains and analyze whether each food access model could help combat malnutrition in underserved communities.

The second research question was answered by collecting 388 surveys from the Somerville residents. These surveys were translated into four languages (English, Spanish, Creole, Portuguese), and were designed to understand the preferences of Somerville residents and their likelihood of using each healthy retail option. This survey was segmented into seven sections: grocery shopping patterns, transport method to and from grocery store, rideshare and grocery delivery services, hypothetical options for getting groceries, farm veggie box (alternative option), grocery shopping budget, and demographics.

To analyze these data, advanced statistical modeling was applied to determine significant factors, differences and to rank food access models depending on customer's profiles. First, a principal component analysis was taken, resulting in 29 components to be used for analysis. Then a preliminary cross analysis was conducted to spot any trends in the data. Interestingly, the cross analysis found that, among car owners, the higher the education level of those surveyed, the more they preferred the ride-sharing model. This was largely due to the manner in which the surveys were conducted (this is addressed further in section 5).

Nonetheless, the logistic regression the researchers conducted afterwards, showed that the veggie box was the preferred option among Somerville residents. It found six factors that lead to the preference of the veggie box model. These will be discussed further in the discussion section, Section 5.1. Lastly, interviews with wholesalers/distributors and farmers/farmer associations showed that the veggie box model is a feasible model to provide food deserts with fresh produce. Moreover, over 70 percent of survey respondents indicated that they prefer the veggie box model and, our logit model was able to describe 89.5 percent of this data.

Following this general overview will be a literature review (Section 2), outlining research that has already been performed surrounding the topic of food deserts and healthy food supply chains. Afterwards is an outline of the methodology (Section 3) used in performing this research. Following the methodology is the results section (Section 4) that shows what was found from the research. The discussion (Section 5) follows the methodology. In this section, the meaning of the results will be discussed. The last section is the conclusion (Section 6). This section will address any shortcomings of the current research and opportunities for further research.

## **2. LITERATURE REVIEW**

The focus of this literature review was to investigate research on the availability, affordability, and accessibility of healthy food options in food-desert areas. To do this, the review targeted four different areas. First, it analyzed food malnutrition and vulnerable population trends in general. This explained why food-deserts were an issue and made clear the impact that they have. Second, the literature review focused on identifying what research has already been done on utilizing ride sharing systems to combat food malnutrition. This is one of the research areas of the project, as it is a proposed method of providing healthy food access to underserved communities. The focus of the third portion of the literature review is the grocery delivery model. This was the focus of the

third portion of the literature review. Finally, the main focus of the literature review analyzed the feasibility of sourcing neighborhood markets with healthy food and the local supply chains implications associated with this method. This is the primary focus of MIT's portion of the capstone. Therefore, an extensive amount of research was allocated to this part of the project. In each of these sections, the researchers found related articles, compared and contrasted the methodologies used in those articles, analyzed the results from the experiments, and identified gaps in the research that might be filled through their own research.

## **2.1 Food malnutrition and vulnerable population trends**

The World Health Organization (WHO, 2016) defines malnutrition as “*deficiencies, excesses or imbalances in a person's intake of energy and/or nutrients.*” Individuals can fit this description by not only having enough to eat, but also by having too much of the wrong types of food (i.e. sugary sodas, candy, and consumer packaged goods that are high in calories, but low in nutrition value). Both of these forms of malnutrition may be consequences of food insecurity -- being without sufficient access to food in general or specifically healthy food options (USDA, 2019).

According to the Food and Agriculture Organization (FAO), the International Fund for Agricultural Development (IFAD), United Nations International Children's Emergency Fund (UNICEF), World Food Program (WFP), and WHO (2019), food-insecurity can be measured in three severity levels: food security, moderate food insecurity, and severe food insecurity. These organizations use two key indicators from the Sustainable Development Goals (SDG) framework to monitor the predominance of undernourishment (PoU) and predominance of moderate or severe food insecurity. In sum, the first estimates the number of people that lack enough dietary energy

while the second estimates the number of people who do not have access to nutritious and sufficient food due to scarcity of resources.

Figure 1 shows that while undernourishment on a global scale had been decreasing for years, that decrease stopped in 2015 and has been growing since. In terms of population, over 820 million people do not have access to food. This situation is similar to the one in 2010, showing no significant improvements regarding the problem.

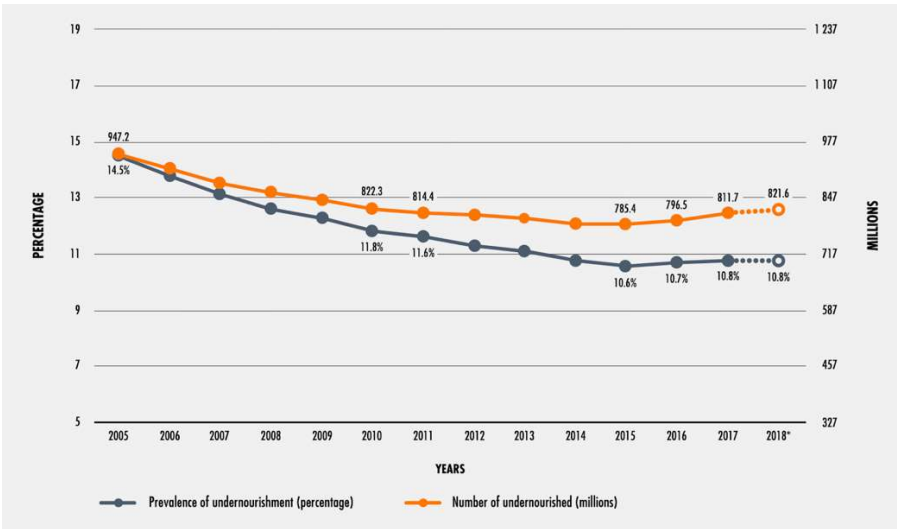
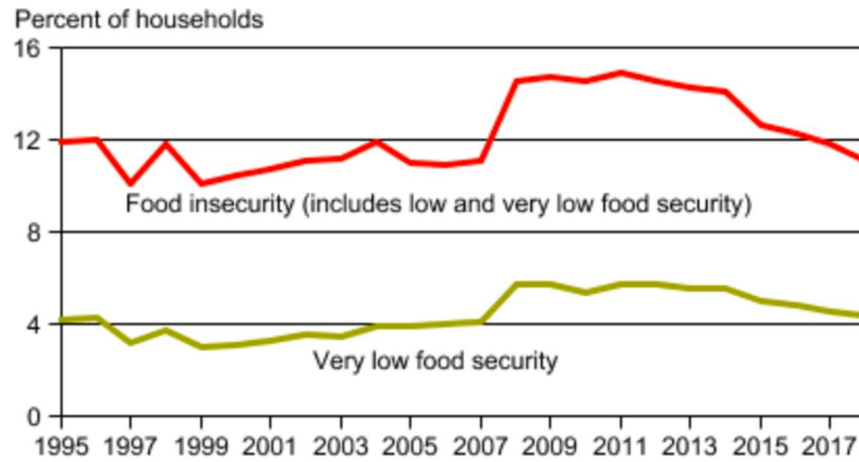


Figure 1. Line graph showing the prevalence and number of the undernourished population from 2005 to 2018. “Food and Agriculture Organization of the United Nations (FAO), International Fund for Agricultural Development (IFAD), United Nations Children’s Fund (UNICEF), World Food Programme (WFP), & World Health Organization (WHO),” 2019. *The state of food security and nutrition in the world. Safeguarding against economic slowdowns.*

This problem is also true in the United States. Here, food insecurity has followed a negative trend since 2012 (Figure 2).

### Trends in prevalence rates of food insecurity and very low food security in U.S. households, 1995-2018



Note: Prevalence rates for 1996 and 1997 were adjusted for the estimated effects of differences in data collection screening protocols used in those years.

Source: USDA, Economic Research Service, using data from Current Population Survey Food Security Supplement.

Figure 2. Line graph showing the trends in prevalence of food insecurity and very low food security in the US from 1995 to 2018. “USDA, Economic Research Service, using data from Current Population Survey Food Security Supplement.”

## 2.2 Ridesharing systems to combat food malnutrition

As mentioned in section 2, food accessibility is an important factor when considering food malnutrition. Access to healthy food is usually constrained by the socio-economic level of a population. Consequently, low-income areas have a higher probability of being food-deserts. These underserved populations might not have healthy options close to their home or work, nor a means of transportation to those grocery stores selling healthy food.

Allcott et al. (2017) studied the sources of “nutritional inequality” to understand the impact of income on eating habits in the United States. They investigated the behavior of low-income

populations in food-deserts by studying two factors: access to supermarkets and purchase patterns with local suppliers. As a result of their research, the findings showed that the mitigation of food-deserts does not significantly improve the eating habits of underserved population. However, subsidies for healthy foods provide a better outcome.

Recently, Uber and Lyft have been partnering with local governments and NGOs to complement their support to low-income families in food-deserts, providing rides to and from grocery stores. According to both companies, affordability and reliability of transport are likely to positively impact the lives of the population living in these areas (Uber Newsroom, 2019; Lyft Grocery Access, 2019).

While Allcott et al. (2017) argues that the lack of access to healthy options is not relevant in diminishing the problems associated with food-deserts, Uber and Lyft are still expanding their programs to several cities in the United States. However, there is no research investigating how ridesharing is able to give broader access to healthy foods for residents of food-deserts.

### **2.3 Grocery delivery via mobile, fresh trucks and Instacart**

Another strategy for making healthy food accessible for food-desert residents is to utilize recently popularized, online grocery delivery services. In this case, patrons would place their grocery orders online, either through a third-party app (such as Instacart) or directly to a supermarket such as Walmart, Kroger, or BJ's Wholesale Club. Since these stores have begun offering these services, they have promised to service a greater number of customers and match changing shopping habits (Bauerova, 2018). While this option might improve food access for many people, there are some barriers when considering low income populations that live in food-deserts.



The article Online Grocery Delivery (MMR, 2018) addresses the launch of online grocery delivery services for several grocery stores including Walmart, Kroger, and BJ's. It specifically mentions some of the investments Walmart has made for the new service. In particular, Walmart has created a 3-week employer training module to support their employees in selecting high quality produce and meats to deliver to customers. They also address how Walmart will transfer the groceries to customers. Walmart plans to use crowd-sourced ride-sharing services such as Uber or Lyft for delivery. All of these changes result in an additional cost. In particular, Walmart's delivery fee for these products is \$11 with a minimum order amount of \$30 worth of goods. This particularly high delivery fee might make it difficult for a lot of food-desert residents to utilize this service.

William Salter (2014) discussed how this issue of price sensitivity might be an issue for online grocery delivery in the United States. He found that the investment costs that US companies would have to make would be very large. Moreover, he showed how there is a shortage of drivers to transport the goods in the United States. Therefore, there will be a higher charge to transport groceries to households. This means that households that wish to utilize online grocery delivery will have to pay a premium to use this service.

This subject of delivery charge is particularly important. In *Consumers' Decision-Making in Online Grocery Shopping: The Impact of Services Offered and Delivery Conditions*, Bauerova (2018) discusses the most important factors to customers when shopping for groceries online. After interviewing 536 online grocery shoppers in the Czech Republic, Bauerova found that the most important factors to customers were delivery cost and the time it took to deliver the food. In fact, these were particularly sensitive factors. If the cost or the delivery time was too high, customers were deeply dissatisfied with the service. Other factors such as the minimum order amount required for delivery were not very significant in changing how customers interacted with the

grocery store. This further shows how customers tend to be particularly price sensitive when it comes to the cost for delivery. However, since minimum order quantity is not a sensitive factor, if the order quantity is increased further, companies might still be able to make a profit without charging such high delivery fees, comparatively.

Some companies have opted to utilize crowd-sourced ridesharing services for the delivery of their groceries. However, there might be an added difficulty to utilizing these services, particularly for many urban food-deserts. Ta, Esper, and Hofe (2018) used social identity theory as a premise to their research. Many crowd-sourced delivery services utilize identifiable information so the person receiving the delivery is aware of who is making the delivery. The hope is that this additional information will improve the customer experience. In *Designing crowd sourced delivery systems: The effect of driver disclosure and ethnic similarity*, Ta, Esper, and Hofe found that providing identifiable information about the driver making the deliveries only improves customer experience when the driver is similar to the person who placed the order. There was a particularly high correlation between customer satisfaction and the ethnicity of the driver -- if the driver and the customer had the same ethnicity, customer satisfaction increased. Otherwise, customer satisfaction decreases. These results align with many recent reports about racial discrimination for crowd-sourced delivery and rideshare services. This is important to consider for food-desert grocery delivery solutions, as many people in urban food-deserts are racial or ethnic minorities.

## **2.4 Short, local food supply chains and subscription-based models via neighborhood markets**

Another strategy to increase the amount of healthy foods available in food-deserts is to utilize the neighborhood markets that are already present. These are the locations where many food-desert residents, particularly low-income residents, tend to do the majority of their grocery shopping. This solution allows residents to continue their normal food shopping habits but provides them with more healthy options to choose from. The following sources provide an in-depth look at the research that has already been done, to assess the feasibility of this option from both the consumer perspective and the neighborhood markets' perspective. First the various pieces of research conclude that many neighborhood corner stores do not currently offer enough healthy food options. The research then shows that residents in food-deserts have similar demand for healthy food options as do areas with access to healthy foods (food oases). Moreover, these residents tend to place a high value on having low prices and the quality of the food that they purchase in the corner stores. This provides some difficulty for neighborhood markets to source healthy food products at affordable prices. Many neighborhood markets fear that their current patrons will not purchase the healthy food options they provide. The research also assesses how advertising the availability of healthy food options at corner stores, as well as the accessibility of Supplemental Nutrition Assistance Program (SNAP) and Women Infants and Children (WIC) program benefits to offset the cost of food, affects consumer consumption of healthy products.

*In Identifying Corner Stores as the Future of Healthy Food Access in African American Communities*, Romano, Lee, Royal, Metz, Ruth, & Hartsook (2017) performed some analyses on Mecklenburg County, North Carolina. They found that of the 230 census tracts in the county, 113 of them are without a full-service grocery store (defined as a grocery store providing fresh produce,

fresh meat, fresh dairy, and processed foods). Of those without a full-service grocery store, 37 census tracts contained a corner store. All of these census tracts were located in low-income, predominantly African-American communities. This information shows how, in many areas, low income and minority communities might particularly benefit from sourcing corner stores located in food-deserts with healthy foods. This study does not go into the methods for sourcing these corner stores, what difficulties the stores might have in selling this food, whether or not consumers will purchase these foods, or other analysis about how this phenomenon affects other racial and ethnic groups.

O'Malley, et. al. (2013) conducted some research specifically about increasing healthy food access in food-deserts in his article *Feasibility of Increasing Access to Healthy Foods in Neighborhood Corner Stores*. He described challenges for the corner store both from the sourcing side as well as from the demand side. The article discussed that produce wholesalers see little profitability in selling the relatively small amount of produce that corner stores would require for their customers. Corner store owners stated that customer demand, cost of produce, and in-store infrastructure were barriers for them to offer more healthy foods. Contrarily, however, customers indicated that they would purchase more fresh fruits and vegetables if those options were available in their local neighborhood corner store. The methods used to gather the data that show these results included 97 household interviews and 24-hour dietary recalls. Researchers also conducted interviews with 60 corner store customers and 12 corner store owners and/or managers. This data was collected in three New Orleans neighborhoods that did not contain a supermarket. This article did not test alternative methods for neighborhood markets to source produce and other healthy foods, outside of produce wholesalers. There was also no assessment of profitability for corner

stores sourcing and selling healthy foods. This would be helpful to assess the feasibility of using corner stores as a means of getting healthy food products into food-deserts.

In *Access to Healthy Foods in Rural Minnesota: A Pilot Analysis of Corner Stores*, Larson, Mullaney, Mwangi, Xiong, Zielgler, (2017) found that corner stores in Nicollet County, Minnesota tended not to offer a significant amount of healthy options. They came to this conclusion using the following methodology: First, they identified several corner stores that should be included in the study. Next, they selected several Auditors that would enter stores and collect data and trained them on what to look for and how to collect the data. The auditors then entered 24 different corner stores, asking questions about the quantity, quality, and cost of the healthy food options available in the stores. They also asked about the availability of SNAP and WIC and noted if/how stores advertised that they accept these benefits. All of these data were collected for analysis which lead to the aforementioned conclusion -- that corner stores in food-deserts do not provide a large enough quantity or variety of healthy foods for its customers. This study, however, did not provide a thorough analysis of what could be done to increase the availability, purchase, and consumption of healthy foods at neighborhood markets.

A different study in eastern North Carolina found “no significant associations between the healthfulness of food store offerings, customer purchases, or dietary consumption” (Pitts, 2017). The methodology used to come to this conclusion was as follows. The research surveyed 479 customers who shopped in at least one of 16 different corner stores. The survey asked questions about the customers’ demographics, food purchases, shopping patterns, and self-reported fruit, vegetable and soda consumption. After collecting this data, the researchers used Pearson’s correlation coefficients and adjusted linear regression analyses to asses if there was an association between healthy food offerings, customer purchases, and what customers eat. While the North

Carolina legislature did spend \$250,000 to help corner stores provide healthier food and beverage options, there was no assessment of the store's offerings. This study did not study the availability or quality of healthy foods offered in these stores. It also did not do an analysis on the price of these options and the price point customers needed to make the purchases. There was no analysis on how well the healthy food options were advertised or if SNAP or WIC benefits were offered to customers.

A separate study in New York found an increase in the purchase of healthy food items by changing specific corner store practice. In the research article *Healthy Bodegas: Increasing and promoting Healthy Foods at Corner Stores in New York City*, researchers found that corner stores were an effective and important method of providing access to healthy foods for people living in food-deserts (Dannefer, 2012). The research mentioned noticing “4 changes on a 15-point criteria scale.” The most common changes included placing refrigerated water at eye level so that it is one of the first beverage options consumers see, providing more SKUs of canned fruit that do not contain added sugar, offering healthy sandwich options, and being able to assist customers in identifying healthier food options. All of these changes resulted in a 5% to 16% increase in healthy food purchases among customers surveyed. These purchases include options that were specifically identified as being healthier options. This study shows that customers who might not know what healthier food options are would be more prone to purchasing healthier food options if that information was readily available. One gap in this study, however, is in identifying the best methods to introduce customers to which foods are healthy and which are unhealthy options.

Another research study by Larson C, et. al. (2013) attempted to identify if and why food-deserts struggled to provide healthy foods and why residents did not purchase the healthy food that was provided. Methods used to gather this research were as follows: The researcher selected five

corner stores located in food-deserts in Nashville, Tennessee. These areas were all low-income, but ethnically and racially diverse. From there, the researchers held community listening sessions where they collected data. They also collected data from proprietor surveys, store audits, and customer-intercept surveys. From analysis of this data, this research found that few stores offered healthy foods (specifically, fresh fruits, fresh vegetables, low-fat or non-fat milk, 100% whole-wheat bread) and none of the stores tested offered all four categories. This study centered on a community-oriented approach to addressing the food-desert problem. It did not, however, discuss steps corner stores could use in establishing more trust among residents, educating residents about what healthy food options were, or advertising healthy food options to increase sales for these items.

Mui, Lee, Adam, Kharmats, Budd, Nau, & Gittelsohn (2015) map the sources that many neighborhood markets use to purchase healthy and unhealthy foods to sell in their stores. In particular *Healthy vs Unhealthy Suppliers in Food-desert Neighborhoods: A network analysis of corner stores' Food Supplier Networks* finds that both the unhealthy and healthy supplier networks that corner stores use include wholesale clubs (i.e. Sam's Club and Costco Wholesale). They also found that corner stores' unhealthy supply networks include a variety of stores. This means that it is very easy for these stores to purchase unhealthy products for resale. Contrarily, the healthy supply networks are not as diverse. This is a barrier to sourcing more healthy foods. The research also showed that neighborhood store owners had a misconception about what foods their customers demanded. They were under the false impression that their customers did not have demand for healthy foods, when in fact, they did. The neighborhood markets tend to be family owned and rely on small margins in order to be successful. This article did not test ways for corner stores could source more healthy options, although it did suggest bulk joint ordering among several stores as a

possible, untested solution. This seems to be a viable option because corner stores in the same area tended to source products from the same places.

Another interesting piece of research analyzed store sales data specifically for corner stores that had been assisted by a corner store intervention program (a program that works with corner stores to help them provide healthy food options). In *Exploring sales data during a healthy corner store intervention in Toronto: The Food Retail Environment Shaping Health (FRESH) project*, Minaker, Lynch, Cook, & Mah, (2017) collected sales data on local corner stores. This data was aggregated by product category and by day. They then analyzed this data using t-tests to examine differences in peak vs non-peak sales days. They found that the peak sales days correlated with issuance of social assistance payments and with transit pass sales. Importantly, sales of fresh fruits and vegetables represented an increase in revenue on these days. This means that analyzing sales data is an important metric to consider when assessing the effectiveness of corner store intervention programs. It also shows that there is a correlation (even among healthy foods) among sales and social assistance program payments. This analysis does not directly test whether or not offering more social assistance programs in stores will cause more sales of healthy foods.

In Paluta, Kaiser, Huber-Krum, & Wheeler's *Evaluating the Impact of a healthy corner store initiative on food access domains* (2019). They found that healthy corner store initiatives resulted in more patrons coming into corner stores, and more sales for healthier items. They reached this conclusion by evaluating Fresh Foods Here's (a Healthy Corner Store Initiative) network in Columbus, Ohio. They collected data from invoices, inventories, rapid market assessments, and customer surveys. They analyzed this data to find changes in food access and corner store service. This paper does not do an analysis of the causes (i.e., advertising, SNAP/WIC benefits, methods for identifying healthy food options, etc.) that resulted in these positive results.



In order to combat food malnutrition and its current deterioration in recent years, academics have been researching different options to address this issue and provide a healthy life to every citizen independently of their family income. They have analyzed this situation through different approaches that can be segmented in ridesharing systems, grocery deliveries, and different uses of neighborhood markets. However, the feasibility analysis of these diverse strategies applied in a low-income area has not been explored until this moment, particularly in Somerville, MA. This is one way in which the authors of this research will fill a gap left in the research that is currently available.

Another gap that is being filled with this paper is an analysis of a supply chain model that could actually source food desert communities with fresh produce. This supply chain model considers the producers (farmers) all the way to the end consumer (Somerville residents). This paper also conducts a sophisticated statistical analysis of the diverse food access models that were proposed and assembled by the researchers, based on the literature review. This is yet another gap that this research fills. Lastly, for the first time, this research actually gauges the feasibility of several potential models and provides a method for determining the best one. These additions to the body of research already available will expand the knowledge of how to source residents of food desert communities.

The research for this paper first analyzes the key stakeholders of a food supply chain through open question interviews and, second, surveys the local population of Somerville to assess their preferences. Lastly, this research proposes a model to improve the current situation in the study area and assess the replicability of this model to other low-income areas.

### **3. DATA AND METHODOLOGY**

In order to answer the two research questions (i.e., How feasible is each of the food supply chain models to increase healthy foods in low-income areas? Which food supply chain model will residents of low-income areas prefer?) the researchers took several steps. First, they engaged in a process and stakeholder mapping. This provided insight into the various stakeholders in each of the models. Second, the researchers designed the interview and survey questions. This process was done with great care to ensure the information needed would be provided and also to be sure that those being interviewed or taking the survey felt comfortable enough to give complete and honest answers. Afterwards, the data were collected by conducting interviews with each tier in the supply chain (farmers/farmer associations, wholesalers/distributors, neighborhood market owners and managers) and surveying the residents of Somerville, MA. Next, the data were cleaned and processed in order to prepare it for analysis. This provided the correct framework to do a descriptive analysis followed by more in-depth analyses of the data. After the descriptive analysis and cross-analysis, a principal component analysis and logistic regression were performed for further analysis.

#### **3.1 Process and Stakeholder Mapping**

The first step was to identify the processes for the neighborhood supply chain model, specifically the veggie box model. This would include the neighborhood market perceiving a demand for these veggie boxes and also receiving them at a price where they could be profitable. From the literature review, it was clear that wholesalers presented a barrier for neighborhood markets to receive produce. Therefore, it would be important to gauge this feasibility. Another option would be to see if farmers would be willing to sell directly to neighborhood markets.

From this reasoning it was clear there were four tiers of stakeholders whose preferences needed to be identified. Specifically, these stakeholders were the end consumers, the neighborhood market owners/mangers, the wholesalers/distributers, and the farmers/farmer associations. It was determined that the best way to get these answers would be to do field interviews with the neighborhood market mangers, wholesalers, distributers, farmers, and farmer associations. There are only a few of each of these and their preferences would be more or less similar, given that they are delivering services at a similar scale. In contrast, however, the end consumer preferences might differ greatly. Therefore, it was important to reach a large and diverse number of end consumers. The best method of getting this data would be from an online survey distributed by a trusted messenger. In this case, the trusted messenger was the Somerville city council.

### **3.2 Design of the Interview and Survey**

The design of the interviews and surveys was extremely important. For the survey, it was important to capture three key aspects. First, the survey needed to capture the consumer preferences for the various methods of accessing healthy food. Second, the survey needed to capture the demographic information of each respondent. This would allow the researchers to see how these differences might impact consumer preferences. Lastly, the survey needed to capture the availability, affordability, and accessibility consumers had to fresh produce. The survey was translated into four different languages to ensure that everyone in the Somerville community would have access to the survey and the data collection would be more complete.

The interviews had a different objective. After observing the results of the consumer survey, we needed to see if it would be feasible for the upstream supply chain to meet their demands. These questions focused on the logistics of their operation, what their supply and demand looked like, what products they sold, whether a veggie box model would work for their

business, and whether or not they had interest in serving low-income communities. All of these questions were specifically chosen to get insights into the feasibility of implementing the veggie-box supply chain model in food-deserts in Somerville, MA.

### **3.3 Data Collection**

The data collection was carried out in two different ways: 1) The researchers partnered with the city of Somerville to distribute the survey to residents of Somerville (i.e., the end consumers), and 2) The researchers interviewed 17 different stakeholders in the various supply chain models. These interviews included wholesalers/distributors, farmers/farmer associations, ridesharing systems, grocery delivery services, and neighborhood markets. For the veggie box model, the focus of this research, the research included 388 surveys, four interviews of farmers/farmer associations, one interview with a wholesaler/distributor, and five interviews with neighborhood markets. While there were only four interviews from farmers/farmer associations, the farmer associations are able to speak on behalf of each of the farmers that they work with. This provides insights into how several farmers would utilize the models, even if it consisted of just one interview.

Specifically, the farmers' associations interviewed worked with 44 large scale/business level farms as well as 473 smaller scale farms. The interview with the wholesaler/distributor provided a lot of information. However, only one company in this category was interviewed due to the difficulty of contacting wholesalers and distributors. The five interviews with corner stores were representative. These interviews were in different locations in the city, serving different segments of the populations, and had different scope of products served (including produce). The

researchers felt confident that this number of interviews captured provided a lot of useful information for the research.

These surveys were administered in random locations across the city including senior centers and other shelters, however, 70% of the surveys were collected in supermarkets across Somerville. There was also an incentive provided to survey takers. They would be entered into a drawing for a gift certificate if they decided to take the survey. The survey included 41 questions segmented in seven categories addressing grocery shopping patterns, transport method to and from grocery store, rideshare and grocery delivery services, hypothetical options for getting groceries, farm veggie box (alternative option), grocery shopping budget, and demographics (Appendix 1). There were 388 responses to the survey from Somerville residents.

The interviews were obtained by phone for wholesalers, distributors, farmers and farmer associations. They were standardized in that each of the questions listed in the Appendix 2 were asked. However, if the interviewee provided extra information, that information was recorded as well. These individuals were not offered any incentive to engage in the interview.

The managers/owners of the neighborhood markets were interviewed at their own stores. This allowed the researchers to see the store in person, identify if they provided fresh produce and what quantity was available in the store. By doing in-person interviews, the researchers were also able to analyze the layout of the store, observe the in-store operations, and identify the most frequently bought products. These interviews were not easy to obtain for several reasons. First, it was important for the researchers to speak with the manager or person who is responsible for the store operations in order to get accurate answers to the survey questions. In many nanostores, this person does not always come into the store to work every day.

Another barrier is trust. Store managers might not be very eager to provide intimate details about their store operations for fear that a competitor will utilize this information against them. Lastly, many of the store owners were most comfortable speaking in languages other than English. Even with all of these barriers, the researchers were able to still obtain 17 interviews by building trust and rapport with the store owners and ensuring that the purpose of the questions were purely for research purposes. This assisted in the analysis of the feasibility of the veggie box model. These questions, which are listed in Appendix 2, were also standardized and the questions were listed in the Appendix 2. Upon completion of the interview, the manager was offered a \$100 gift certificate as a thank you for their time.

Each of these interviews gave the researchers a plethora of information. Those who were interviewed provided first-hand knowledge from their experiences. Their insight indicated what supply chain models would be feasible for their business and which models would not work. All of this information helped the researchers answer the first research question: What is the feasibility of each food supply chain (grocery delivery, rideshare, veggie-box) to increase healthy foods in low-income areas?

### **3.4 Data Cleaning and Processing**

The data cleaning step was particularly important. The survey included 41 questions, many of which offered the respondent the ability to select multiple answers. Moreover, the researchers received 388 responses. This created a lot of data to analyze. Inevitably, some of the responses were incomplete and needed to be cleaned. This cleaning included removing blank responses, combining questions that provided similar information, questions, and deleting questions that were unnecessary for this portion of the research project.

The researchers took a systematic approach to identifying which questions were pertinent and which could be vetted. First, they removed blank questions. Then, they removed questions that were duplicates, or that provided similar pertinent information. To decide which information was pertinent, the researchers considered what information was directly related to the research question this survey sought to answer (i.e., Which food supply chain model would residents of low-income areas prefer?). All demographic information was retained since this would be important for the descriptive analysis. All free response questions were removed since these would be too difficult to analyze in a quantitative manner. Sometimes questions were elongated, with more answers than what were necessary for the research, simply to ensure that the respondent could answer the question with confidence.

For example, question 10 of the survey asked “Most of the time, what transportation do you use to get to the store when you buy your groceries?” The responses to this question included Walk, Bus, The T, Bike, Household car, taxi, Lyft or Uber, Borrow a car from a friend/family member, Drive with a friend/family member, The RIDE, motorized chair, and other. The only information the researchers needed from this question was to 1) gain an understanding of which means of transportation residents typically use or have access to in order to get their groceries and 2) how would each transportation type fit within the three proposed grocery supply chain model.

Since this information is all the researchers really needed, they narrowed their answers into simpler categories. 1) Public transportation such as the T, the RIDE, and bus 2) Self-transportation without a vehicle, including Walk, Bike, and Motorized Chair 3) Ridesharing Services like Taxi, Lyft or Uber and 4) Personal automobile including utilizing a household car or driving with/borrowing a car from a friend or family member.

If these categories were grouped together initially in the survey, it might confuse the respondents. However, if the responses remained disaggregated there would be many more factors to analyze, unnecessarily complicating the data analysis without providing any additional useful information.

### **3.5 Descriptive Analysis**

It was also important for the researchers to get some descriptive statistics for the survey conducted. There were two pieces of data used for the descriptive analysis. The first was simply the entire dataset. This gave the researchers insights into the breadth of the data and the baseline information about Somerville. The second was a subset of the dataset. This research was focused on the neighborhood markets. Therefore, the second descriptive analysis specifically targeted survey respondents who indicated that they visited neighborhood markets to do their shopping 2 – 3 times per month or more. The researchers are particularly interested in the behaviors of people who shop in neighborhood markets often enough to use the veggie box model, so it was important to take a special look at the demographics of this group.

### **3.6 Principal Component Analysis and Logistic Regression**

Due to the nature of the survey, there were a lot of variables to be analyzed. Since many of the questions were multiple choice “select all that apply” questions, one question could result in dozens of variables. There were 225 total variables in the raw data from the survey. This is too much information to do sophisticated analyses. Furthermore, the researchers needed to find a way to pull out the important information from the variables collected in the survey. The researchers did this by conducting a principal component analysis (PCA) in order to reduce dimensionality and to model unsupervised data that came without corresponding responses. Its goal is to find patterns and structure in the data. After identifying the principal components, the researchers could



perform a logistic regression on the data. The PCA brought out the relationships between the survey questions/responses and the relevant pieces of this entire dataset. This helped the researchers answer the second research question: Which food supply chain model will residents of low-income areas prefer?

## 4. RESULTS AND ANALYSIS

### 4.1 Descriptive Statistics

Table 1 shows the shopping habits of the survey respondents. Of the respondents, 51.5% indicated that they shop at Neighborhood Markets at least once per month. Moreover, 34.2% of respondents shop at neighborhood markets frequently (2 – 3 times per month or more).

Table 1. Number of Shoppers by Frequency and Location

	Never	< 1x a month	1x a month	2-3x a month	Once a week	+2 times a week	Daily
Neighborhood Markets	33.8%	14.7%	17.3%	14.3%	9.8%	7.1%	3.0%
Grocery Stores	13.2%	0.4%	1.9%	3.4%	12.0%	40.6%	27.4%
Others	35.7%	11.3%	19.2%	16.9%	12.4%	4.1%	0.4%

Table 2 shows the travel time to the grocery store below. It shows that 44.7% of the survey respondents have more than an 11-minutes commute to their closest grocery store.

Table 2. Travel Time to a Grocery Store

Time	Percentage
0-10 minutes	55.3%
11-20 minutes	36.8%
21-30 minutes	5.6%
31-40 minutes	1.5%
40 minutes or more	0.8%

Moreover, 22.2% of the respondents also do not have access to a household car.

Table 3. Possess Household Car

Car Ownership	Percentage
Yes	77.4%
No	22.2%

The survey asked if people have had concerns about not having enough money to buy food. This was broken into two questions: first, how often residents had been worried whether their food would run out before they received money to buy more; and second how often the food they bought did not last and they did not have money to get more. The results of these questions are below in Table 4, which shows that 8.6% of respondents have worried about running out of food, and 6.0% of respondents have actually run out of food before having money to buy more.

Table 4. Financial Concerns Around Food Security

Concern	Never True	Sometimes True	Often True
Worried whether our food would run out before we got money to buy more	91.4%	7.1%	2.0%
The food we bought just didn't last and we didn't have money to get more	92.0%	4.9%	1.1%

The survey also captured a lot of demographic data. This ensured the researchers would know the groups of people that they were surveying and identify the most affected population groups. The data show that those surveyed were overwhelmingly women (Table 6, 72.2%). They also tended to be young and middle-aged adults (Table 5, 78.6% of those surveyed were between 23 and 4 years old). Also, from Table 7, 61.7% of those surveyed had a master's degree or higher and 30.5% had a college degree. Lastly, Table 8 shows that 79 % of those surveyed were White (not Hispanic).

Table 5. Demographic Data: Age

Age	Percentage
Under 23	1.5%
23-38	46.8%
39-54	32%
55-73	16.2%
74-91	3.8%

Table 6. Demographic Data: Gender

Gender	Percentage
Male	22.2%
Female	72.2%
Non-Binary	2.3%
Prefer not to answer	3.4%

Table 7. Demographic Data: Educational Level

Education level	Percentage
Less than High School	0.4%
High School Diploma or GED	2.6%
Some College	4.9%
College Degree	30.5%
Master's Degree or Higher	61.7%

Table 8. Demographic Data: Race/Ethnicity

Education level	Percentage
Asian	5.6%
White	79%
Hispanic	2.7%
Black or African American	1.9%
Other	11.0%

The sample of this research is predominant female, white, 23-54 years old, high level education, and owns car. Besides this, the respondents shop groceries in grocery stores more frequently than any other option. To have a better understanding about the characteristics of the respondents and their preferences, a cross-analysis was performed in the next section of the aforementioned variables that are directly related to the research questions.

## 4.2 Cross-Analysis

As mentioned in the literature review (section 2), there are three main factors that are the core problem of malnutrition: accessibility, affordability, and availability. Additionally, studies mentioned in the same section also highlighted constraints regarding the access to healthy foods and how it modifies the consumer patterns. Considering the objective of this research project, a cross-analysis of commute time and shopping frequency with a layer of adopting a specific food supply chain model was performed (Appendix 4, 5, and 6). This cross-analysis provided an initial understanding of the relationship between the variables related to this sample and the studies mentioned in the section 2.

This preliminary analysis showed that consumers who have a shorter commute and shop frequently in grocery stores are less likely to accept low-cost ride sharing and grocery delivery solutions while the result is the opposite for the veggie box model based on the proportion of cases within three variables and as showed on Appendix 4, 5, and 6.

Another interesting insight from the cross-analysis was the relationship of using ridesharing services even though the respondents own a car. As mentioned in the previous section, over 92% of the sample have a college degree or a higher degree and over 70% of the respondents with this education level own a car, but they prefer to use ridesharing services. The results of this exploratory analysis led the researchers to investigate in the next sections if the preference for a low-cost ridesharing model would prevail over other models.

Since there are differing results for each of the food supply chain models, and due to the quantity of variables available to research consumer preferences and each model's feasibility, the application of principal component analysis is necessary to filter out variables that do not explain the variability of the results in a large proportion or are irrelevant.

### 4.3 Principal Component Analysis

A principal component analysis (PCA) was performed on the 72 independent variables generated from the survey applied in Somerville, MA. Due to the quantity of variables, the visual inspection of the scree plot below (Figure 3) was not helpful for indicating the quantity of variables to be retained.

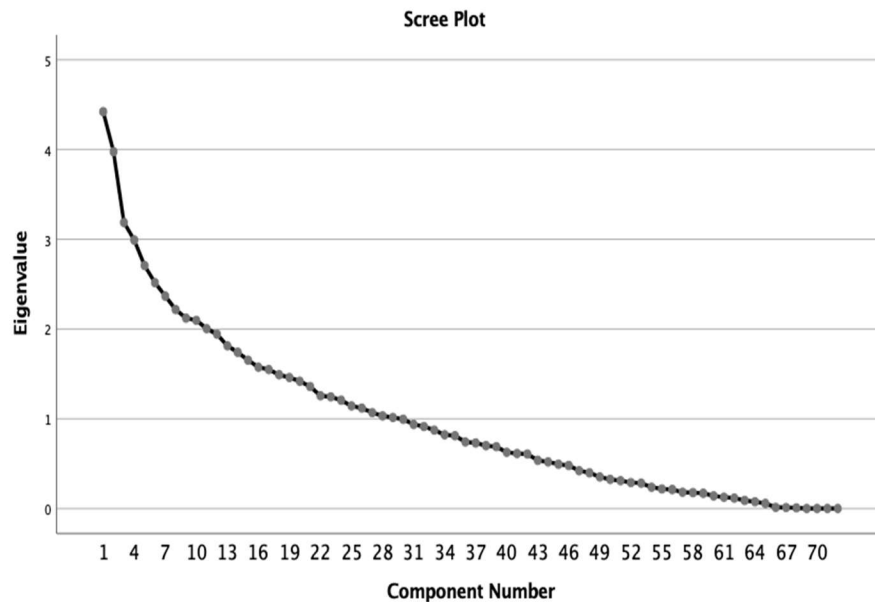


Figure 3. Principal Component Analysis Scree Plot showing the number of principal component variables (x-axis) that should be used for analysis.

Based on this situation, the components with eigenvalues greater than one were selected through PCA, as these were the components that described the majority of the data. As a result, 29 components explained over 77.35% of the total variance (Appendix 10). The first five components consist of a set of variables that helps most to explain the variability of the models. As it can be seen below, transport methods (component 1, 2, and 5), age (component 3), grocery shopping for members of family with a specific age (component 3 and 4); and commute time, concerns about not having food and money, and educational level (component 4) are the main elements.

The survey had a higher representation of respondents between the ages of 23 and 54 years old (Table 6), females (Table 7), and a high-level of education (Table 8). The principal component analysis corroborates the findings of the descriptive analysis section, as these variables are also included in the top 5 PCA components. Additionally, the transport methods variable listed as part of components 1, 2, and 5 is indirectly related to the commute time of the respondent, a variable that considerably affected the likelihood of using a food supply chain model as shown in the cross-analysis section. The logistic regression model was able to dictate the level and direction of the influence of each component on the dependent variable. For instance, analyzing the variables individually of the component 1 shows that walking from and to a store may favor the adoption of a food supply chain model if the component has an  $\text{Exp}(B)$ <sup>1</sup> over 1.0 in the logistic regression analysis (Section 4.4.4).

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<sup>1</sup>  $\text{Exp}(B)$  communicate the changes in the odds for each increase or decrease per unit of the independent variable. Values lower than 1 result in a decrease while values above 1 mean an increase.

Table 9. Top Five Components

Component	Survey Question	Name	Variable Code	Strength
1	Q10	Walk	IV13	0.922
1	Q10	Walk and Vehicle	IV18	-0.396
1	Q10	Vehicle	IV23	-0.333
1	Q12	Walk	IV27	0.895
1	Q12	Walk and Vehicle	IV34	-0.386
1	Q12	Vehicle	IV40	-0.358
1	Q18	Household Car	IV51	-0.478
2	Q10	Walk and Vehicle	IV18	0.807
2	Q10	Vehicle	IV23	-0.845
2	Q12	Walk and Vehicle	IV34	0.806
2	Q12	Vehicle	IV40	-0.838
3	Q28	Selection of Vegetables by Someone	IV56	0.387
3	Q36	Grocery for 19-60 years old	IV67	0.682
3	Q36	Grocery for over 60 years old	IV68	-0.879
3	Q39	Age	IV69	-0.769
4	Q13	Commute	IV43	0.330
4	Q33	Food Run Out	IV63	0.867
4	Q33	No Money and No Food	IV64	0.858
4	Q36	Grocery for 6 to 18 years old	IV66	0.430
4	Q40	Educational Level	IV71	-0.381
5	Q8	Other Location for Grocery	IV12	0.625
5	Q10	Walk, Bike and Vehicle	IV25	0.952
5	Q12	Walk, Bike and Vehicle	IV42	0.952

The correlation matrix, communalities, component matrix, rotated component matrix, component transformation, and component score coefficient may be found in the Appendices 8, 9, 11, 12, 14, and 15. The usefulness of correlation matrix when performing a PCA is related to the approach of taking standardized form of the inputs, eliminating any risk of using variables with different scales. The communalities table represents the proportion of common variance originated from a particular variable and goes from 0 to 1 (FIELD, 2013).

The component matrix represents the strength of the correlation of specific variables with a component. The rotated component matrix is the result of the rotation of the frame of reference with the purpose of maximalization of the dimensions while the component transformation matrix shows the correlations before and after the rotation, highlighting the improvement. Lastly, the component score is calculated from the multiplication between the standardized values and the component score coefficients. The results of this multiplication were added to the dataset in order to be served as an input for the logistic regression.

#### **4.4 Logistic Regression Model**

With the number of dimensions reduced through the previous analysis, a binomial logistic regression was applied for each food supply chain model as a dependent variable and the 29 components extracted from the PCA. To better understand the results, this analysis is segmented in four subsections: adequacy of the models, explained variation, category prediction, and contribution and significance of each independent variable to the model. Additionally, each principal component was categorized based on the variables with a correlation stronger than 0.3 (Appendix 13).

##### **4.4.1 Adequacy of the Models**

To assess the fitness of the models, Omnibus Tests of Model Coefficients and Hosmer and Lemeshow Goodness of Fit Test were applied. The first provides the overall statistical significance of the model while the second assesses the adequacy of the model by evaluating how poor the model is at predicting categorical outcomes. In different terms, these tests can prove if the overall model is a good representation of the reality.

The three food supply chain models (low-cost ridesharing, low-cost grocery delivery, and veggie box) are statistically significant ( $p < .0005$ ) in accordance with Omnibus Tests of Model



Coefficients, and are not a poor fit ( $p > .0005$ ) based on the results of Hosmer and Lemeshow Goodness of Fit Test. These results can be seen in Table 10 and Table 11.

Table 10. Omnibus Tests of Model Coefficients

	$\chi^2$	df	Sig.
Low-Cost Ridesharing	104.796	29	0.000
Low-Cost Grocery Delivery	96.509	29	0.000
Veggie Box	85.604	29	0.000

Table 11. Hosmer and Lemeshow Goodness of Fit Test

	$\chi^2$	df	Sig.
Low-Cost Ridesharing	9.664	8	0.289
Low-Cost Grocery Delivery	9.048	8	0.338
Veggie Box	5.951	8	0.653

#### 4.4.2 Explained Variation

The variation of the categorical dependent variable can be explained by Nagelkerke R<sup>2</sup> Square, which is equivalent to the R<sup>2</sup> in a multiple regression. The use of this pseudo r-square instead of the traditional one from a linear regression model is due to the unfeasibility of conserving all characteristics of it. Hence, Nagelkerke R<sup>2</sup> approximates this method for categorical dependent variables. It uses the result of Cox and Snell's R<sup>2</sup> and adjusts to a scale from 0 to 1 (LONG, 1997). The 29 components can explain the variables of the low-cost ridesharing, low-cost grocery delivery, and veggie box models as 46%, 40%, and 48% respectively. Considering the range of the prediction power (0 to 1) and the results mentioned previously, the models seem

reasonable accurate. However, further investigation is needed to discern the analysis per categories of consumer profiles.

Table 12. Nagelkerke R<sup>2</sup>

	-2 Log likelihood	Nagelkerke R2
Low-Cost Ridesharing	215.298	0.465
Low-Cost Grocery Delivery	269.293	0.407
Veggie box	143.058	0.477

#### 4.4.3 Category Prediction

To verify the effectiveness of the model and its prediction accuracy, the predicted classification against the actual classification was assessed. The value of 0.5 was used as cutoff point to predict whether a consumer would accept a specific food supply chain model. This value was chosen as a conventional value considering a binary outcome. When the independent variables were added to the models, they correctly classify 82.7%, 75.2%, and 89.5% of circumstances overall with a sensitivity (i.e., ability of correctly identifying all consumers who would be likely to use the supply chain model, true positive rate) of 55.8%, 67.2%, and 95.6% and a specificity (i.e., ability of correctly identifying the consumers who would not be likely to use the supply chain model, true negative rate) of 93.7%, 81.6%, and 56.1%, as shown in Table 13, Table 14, and Table 15 below (Trevethan, 2017).

Table 13. Category Prediction of Low-Cost Ridesharing

Observed		Predicted		Percentage Correct
		Low-Cost Ridesharing		
		.00	1.00	
Low-Cost	.00	177	12	93.7
Ridesharing	1.00	34	43	55.8
Overall Percentage				82.7

Table 14. Category Prediction of Low-Cost Grocery Delivery

Observed		Predicted		Percentage Correct
		Low-Cost Grocery Delivery		
		.00	1.00	
Low-Cost	.00	120	27	81.6
Grocery Delivery	1.00	39	80	67.2
Overall Percentage				75.2

Table 15. Category Prediction of Veggie Box

Observed		Predicted		Percentage Correct
		Veggie box		
		.00	1.00	
Veggie Box	.00	23	18	56.1
	1.00	10	215	95.6
Overall Percentage				89.5

The results of the category prediction presented in the contingency matrix (Tables 14, 15, and 16) show a strong prediction power of the models based on the overall percentage and true positive power. The prediction power and error can be inferred from the tables above.

#### **4.4.4 Contribution and Significance of the Independent Variables**

A logistic regression was executed to ascertain the effects of the 29 components (Appendix 16, 17 and 18) on the likelihood that consumers will use low-cost ridesharing, low-cost grocery delivery, and veggie box. The logistic regression models were statistically significant,  $\chi^2 = 104.796, p < .0005$ ;  $\chi^2 = 96.509, p < .0005$ ; and  $\chi^2 = 85.604, p < .0005$ . The models explained 46.5%, 40.7%, and 47.7% (Nagelkerke  $R^2$ ) of the variance in using the food supply chain models and properly categorized 82.7%, 75.2%, and 89.5% of cases. Sensitivity of the models was 55.8%, 67.2%, and 95.6% while specificity was 93.7%, 81.6%, and 56.1%.

From the 29 predictor variables, the following factors were statistically significant ( $p < 0.05$ ):

Table 16. Logistic Regression on Low-Cost Ridesharing

	B <sup>2</sup>	S.E. <sup>3</sup>	Wald <sup>4</sup>	df <sup>5</sup>	Sig. <sup>3</sup>	Exp(B)	95% C.I. for EXP(B) <sup>6</sup>	
							Lower	Upper
Factor 4	0.632	0.183	11.925	1	0.001	1.881	1.314	2.693
Factor 6	0.542	0.153	12.538	1	0.000	1.720	1.274	2.323
Factor 13	0.488	0.243	4.020	1	0.045	1.629	1.011	2.624
Factor 15	0.483	0.234	4.268	1	0.039	1.620	1.025	2.561
Factor 16	0.328	0.164	4.028	1	0.045	1.389	1.008	1.914
Factor 17	0.529	0.246	4.621	1	0.032	1.697	1.048	2.749
Factor 25	- 0.827	0.355	5.444	1	0.020	0.437	0.218	0.876

The table 16 displays the factors that are relevant on the low-cost ridesharing model. For instance, increasing the variables that are part of the factors/components 4, 6, 13, 15, 16, and 17 would result in an increase of the likelihood of opting for this model. The conclusion can be seen from the values of Exp(B) showed above.

<sup>2</sup> This column informs the value and type of relationship between the independent variable and dependent variable.

<sup>3</sup> Standard Error associated with the coefficient.

<sup>4</sup> The Wald column show the values used to calculate the p-value (Sig. column)

<sup>5</sup> Number of observations for a specific independent variable

<sup>6</sup> Reflects a range of values which a specific probability (95% in this case) that the output is within it.

Table 17. Logistic Regression on Low-Cost Grocery Delivery

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Factor 4	0.632	0.183	11.925	1	0.001	1.881	1.314	2.693
Factor 11	-0.389	0.162	5.768	1	0.016	0.678	0.493	0.931
Factor 14	2.246	0.860	6.828	1	0.009	9.453	1.753	50.967
Factor 15	0.808	0.197	16.797	1	0.000	2.243	1.524	3.301
Factor 16	-0.500	0.236	4.504	1	0.034	0.607	0.382	0.962
Factor 24	0.504	0.208	5.902	1	0.015	1.656	1.102	2.488
Factor 26	-0.471	0.167	7.908	1	0.005	0.624	0.450	0.867

Regarding low-cost grocery delivery model, the factors/components 4, 14,15, and 24 increase the likelihood of consumers opting for this model. As showed above, the factor 14 increases significantly the chances since its Exp(B) is of 9.453.

Table 18. Logistic Regression on Veggie Box

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Factor 1	0.766	0.338	5.121	1	0.024	2.151	1.108	4.176
Factor 2	0.542	0.234	5.371	1	0.020	1.720	1.087	2.721
Factor 3	0.792	0.199	15.854	1	0.000	2.207	1.495	3.259
Factor 12	0.743	0.254	8.545	1	0.003	2.103	1.278	3.461
Factor 18	0.427	0.205	4.368	1	0.037	1.533	1.027	2.290
Factor 20	-0.380	0.155	5.982	1	0.014	0.684	0.505	0.927

Lastly, the factors 1,2,3,12, and 18 increases the probability of a consumer opting for veggie box when increased and factor 20 works on the opposite direction. In practical terms, a stakeholder interested in any of the three models can start focusing on the variables listed above for each food supply chain model. Based on this sample, these factors are statistically significantly and the increase/decrease of likelihood to opt for a specific model can be understood through the Exp (B) value.

## **5. DISCUSSION**

### **5.1 Survey Analysis**

The results described in Section 4 provide new and promising information to address the research questions initially brought forward at the beginning of the research. The first research question asked, “Which food supply chain model will residents of low-income areas prefer?” The research answered this question by conducting a survey of Somerville, MA, residents. There were 388 Somerville residents who took the survey. To analyze the data, researchers utilized principal component analysis (CPA) to reduce the number of variables to analyze. They then did a cross-analysis to preliminarily compare different relevant factors that came from the CPA. This showed some interesting trends in the data.

#### **5.1.1 Cross Analysis**

First, the cross analysis showed that customers who have both a shorter commute to their grocery store and also shop frequently at grocery stores are less likely to accept the ridesharing model or the grocery delivery model. This makes intuitive sense because they have less of a need for transportation to get their groceries, since they live so close to the store. For similar reasons, they would probably be more interested in picking up the grocery themselves rather than relying

on grocery delivery because they do not have to pay the delivery fee and it also wouldn't take them long to get to the store and do their own shopping.

Interestingly, the cross analysis also showed that those customers with a longer commute to a grocery store and who also shop less frequently prefer the veggie box model. This could be because those customers would rather shop locally than travel a far distance to get their food. Also, if they live further away, this could result in higher ridesharing and grocery delivery fees. The veggie box model allows these customers to select their own groceries, including fresh produce, on their own schedule, while avoiding possible hefty fees. Furthermore, if these individuals shop at grocery stores less frequently, they likely have more groceries that they purchase per trip. This could be more difficult to maneuver when utilizing a ride sharing service and cost much more for a grocery delivery service. This serves as a further deterrent from the ride sharing and grocery delivery models.

Another finding from the cross analysis was the demographic preference for the ridesharing model. It showed that over 70% of respondents with either a college degree or higher and who also had their own personal car still preferred the ridesharing model over the veggie box model or grocery delivery. This was a particularly surprising result, as one would assume that those who have access to their own car would use it as opposed to a ridesharing service. This could be a result of the way in which the data was obtained and the demographics that were sampled.

Approximately 70% of the data was obtained in grocery stores. The highly educated segment of those sampled here might be highly satisfied purchasing their own groceries at the location where they already shop. For these individuals, they would have no incentive to switch to a veggie box model at a neighborhood market because they like their grocery store and have easy access to it. These would not be the customers neighborhood market managers would want to



market to in implementing the veggie box model. These customers also might not want to switch to the grocery delivery model because they value selecting their own groceries. The only model withstanding that allows them to select their own groceries and also keep their same shopping habits is the ridesharing model.

### **5.1.2. Logistic Regression**

After completing the cross analysis, the researchers conducted a logistic regression to identify the significant factors from the survey. The researchers found that consumers had a strong preference for the veggie box. This can be seen from the survey responses. Moreover, the logistic regression explained the most amount of data for the veggie box model. Therefore, the analysis is most accurate for this model as well.

The Logistic Regression on the veggie box indicated that six factors were statistically significant for explaining when consumers chose the veggie box model over the other models. Those factors were Principal Components 1, 2, 3, 12, 18, and 20. In each of these cases, the survey questions that are associated with these components make intuitive sense for why consumers would want to utilize the Veggie box model.

Principal components 1 and 2 showed that if a person preferred walking to purchase their groceries, the veggie box model was the ideal model. This makes intuitive sense as well. If a person prefers to walk to purchase their groceries, they would need to shop at a location close to their homes so they can easily carry their groceries back home. Neighborhood markets are in close proximity to where people live. Therefore, people do not need a car or to utilize public transportation or a rideshare service to get their groceries.

Principal component 3 also showed some interesting results. It showed that people who didn't mind allowing someone else to pick their vegetables for them were more likely to prefer the

veggie box model. This makes sense, as the veggie box requires a third party picking which vegetables are included in the box. Also, component 3 showed that if the person was shopping for people who were in the age range of 19 – 60 they were more likely to pick the Veggie box model and if they were shopping for people older than 60, they did not prefer the Veggie box model. Lastly, in general, the older the shopper was, the least likely they were to prefer the Veggie box model. This could mean that older shoppers (60+) want to have more autonomy over the specific vegetables they consume. Also, individuals over 60 might be concerned that the veggie boxes would have more food than they can consume themselves. Since they are less likely to have children living with them, they would require less food. All of this information is consistent with each other.

Component 12 also has some interesting results. Principal component 12 shows that if the respondent preferred to walk to get their groceries, then they also tended to prefer using the Veggie box Model. This is significant because although some people in the sampled population do have access to cars or other means of transportation, many would still prefer receiving a Veggie box at their local neighborhood market. This also shows that those who were willing to adapt the meals they cook at home based on the groceries they receive each week are more likely to prefer the Veggie box model. This is an unsurprising realization, but significant nonetheless.

Principal component 18 showed that among those who indicated that their mode of transportation to their preferred market changed how much or the type of food they purchase, those individuals also preferred the veggie box model. This is important. If people are walking to corner stores that do not have fresh produce, they would fall into this category. People who have to walk a long distance to get to a grocery store with fresh produce would also fall into this category. This

is particularly the case if they purchase fewer items at that distant store, just so that they don't have to carry as many grocery bags back home.

The last component, principal component 20, represents those who utilize public transportation to purchase their groceries. People who are more likely to do this are also more likely to prefer the Veggie box. This also makes sense for similar reasons above. Carrying a lot of bags onto public transportation can be cumbersome. The Veggie box would alleviate this issue.

This analysis answered the first research question because, not only did it show that the customers prefer the Veggie box model, it also provided insights as to the reasons why. These findings align with the research performed in the literature review but provide a unique solution in the veggie box model that has not previously been addressed. This solution also shows that many customers find different ways to access fresh produce, but these are not ideal situations. Many would prefer the veggie box model if it was available.

## **5.2 Interview Analysis**

The second research question asked, "What is the feasibility of this food supply chain (grocery delivery, rideshare, veggie-box) to increase healthy foods in low-income areas?" To answer this, the researchers leaned on the supply chain stakeholder interviews. This discussion will focus specifically on the veggie-box supply chain. From the end consumer survey, the veggie box was the most highly favored model. Moreover, after running the logistic regression, the Veggie box Model yielded the most accurate results (as seen by the Overall Percentage Correct in table 15)

The farmers and farmer associations were the farthest upstream supply chain stakeholders. They are the individuals who grow and pick the food and have a good gauge on costs. Each of the farmers/farmer associations the researchers interviewed were familiar with the veggie box model

that the researchers proposed. They each also indicated how, logistically, the model was feasible to produce on their end. Moreover, they even indicated that it could be done in a cost-effective manner – a cost that neighborhood markets could afford. However, each of them perceived difficulty in selling the produce from the neighborhood markets’ end of the supply chain. The problems they speculated about were both on the neighborhood markets’ demand side (i.e., the end consumer) as well as the neighborhood market’s capacity to handle fresh produce.

The farmers/farmer associations thought that the neighborhood markets would have difficulty selling fresh produce for two reasons. The first reason is that because they assumed the end consumer would not be interested in the products. One farmers association believed that low-income end consumers would not purchase fresh produce because they were used to eating consumer packaged goods. Therefore, they would be reluctant to change their habits and, even if they were inclined to, those consumers wouldn’t know how to prepare fresh produce, even if they were to purchase it. They also stated that, in general, fresh produce is cost-prohibitive for low-income consumers. However, they had never attempted to use the veggie box method.

Another farmer was also skeptical about the feasibility of sourcing neighborhood markets with fresh produce, but for different reasons. He disagreed that low-income consumers were not interested in purchasing or even unable to cook fresh produce. In fact, he had experience working in a Community Supported Agriculture (CSA) program that delivered veggie boxes specifically to low-income customers. The aforementioned challenges were not a point of difficulty for those consumers.

One way he was able to combat the affordability challenge was by selling a certain type of produce. Having experience selling produce through his CSA program, but also to grocery stores and wholesalers, he noticed that many larger-scale retailers only take certain items. In particular,

these stores care a lot about the aesthetics of the product. Many produce items will be grown perfectly, have perfect taste, and be at perfect ripeness level, but due to the nature of growing vegetables, might be slightly misshaped or discolored. Larger retailers will not pay for those products. Often times these products are then wasted. However, selling this fresh produce in a veggie box for a much lower cost both reduces waste (helping the farmer and the environment), and also gives fresh, high-quality produce to those who would like to purchase these items at a discounted price.

This farmer's skepticism about sourcing neighborhood markets with fresh produce was more around the infrastructure of those stores. He argued that many of these neighborhood markets themselves tended to be low budget and have limited capacity for things like refrigerators and other maintenance items necessary to keep produce fresh until time of purchase. This was the challenge that he saw around sourcing neighborhood markets. However, when considering a subscription-based veggie-box model for patrons of neighborhood stores, he thought this could be feasible. This would eliminate the need for neighborhood markets to hold long-term inventory. If the end consumer had a specific date for picking up their veggie-box this would reduce inventory and spoilage cost for the neighborhood market, provide an extra revenue source for the farmers, and also serve the food-desert community with fresh produce.

The wholesalers interviewed were not very interested in the veggie box model. They drive their profits by selling large volumes of produce to clients. Therefore, they are mostly interested in selling to larger retailers such as supermarkets or large-scale grocery stores like Wal-Mart, Publix, or Kroger, rather than smaller retailers like neighborhood markets. One wholesaler specifically said that it is extremely expensive for them to send small amounts of food to any

specific area. Wholesalers, unlike farmers, were not very optimistic about using the veggie box as a method for supplying low-income food-deserts with fresh produce.

Wholesalers run their business by purchasing very large amounts of produce from farmers, utilizing high volume contracts. They then have to get rid of all of that inventory. Particularly for produce items, holding costs and spoilage costs can be very high. Therefore, Wholesalers need to convert their inventory into sales very soon after acquisition. This requires selling large amounts of items at a time. This necessary volume is not conducive to selling produce to smaller neighborhood markets who do not have the capacity to hold large volume or selection of produce.

On the neighborhood market side, each of the market owners who were interviewed saw the veggie box model as feasible. Many of these markets were already selling fresh produce. Some markets' inventory size was large, but for many others it was small and limited. The market with the largest inventory of fresh produce indicated that they lose approximately 5% of their inventory to spoilage and waste. This is a significant amount if a neighborhood market is running on slim margins. When the veggie box model was described to the neighborhood market owner, he was very excited about the idea because it would reduce this waste. He thought it was a great idea and that this methodology could be an industry standard among neighborhood markets in the future.

Neighborhood markets with a smaller inventory of produce were also interested in the veggie box model. One in particular said it would be a good idea, specifically because they have a lot of repeat customers. Those customers could order a subscription to the veggie box and continue receiving a fresh box periodically, for example, each time they do their grocery shopping. One concern that some neighborhood market managers had was the cost of the box. They indicated that many farmers they have tried to work with in the past had high prices on products or only provided organic products (which tend to be higher in price). Many of their customers are price sensitive

and will not purchase products at this higher price. However, this would be alleviated by the previous discussion of the cheaper fresh produce products that could be sold to price-sensitive customers.

While most neighborhood market owners were interested in the veggie box option, there were some potential challenges in implementing the model. First, many neighborhood markets have a limited budget. As such, they might have a hard time purchasing enough produce to meet the demand of their consumers. Second, many neighborhood market owners are risk adverse. If they have been maintaining a profit carrying the goods they currently have, they have little incentive to make a change. This is particularly the case with produce items that have high inventory holding cost and spoilage cost. However, some of this risk would be alleviated if the veggie box was subscription based. Another issue is proper storage space.

Some neighborhood markets did not have refrigerated sections in their stores that would be conducive to storing produce. Others that did have these sections did not have enough space in those areas to expand their product offerings to make room for veggie boxes. This would be an added capital expenditure cost for the market as well as a possible change in inventory where they substitute another item to make room for expanded fresh produce. While these challenges exist, they are not prohibitive for the veggie box model. This model still is feasible. There is an opportunity for further research to assess the cost analysis of implementing the veggie box model given these additional concerns.

The above discussion shows how the veggie box model is a feasible solution for serving low-income communities with fresh produce, sourced from farmers using fresh, high-quality products that wholesalers and full-service grocery stores do not want to purchase. The discussion

answers the second research question. The veggie box model is not only feasible logistically, but also feasible by cost and is preferable to customers.

## **5.3 Managerial Insights**

### **5.3.1 Managerial Insights from Survey Analysis**

The biggest managerial insight from the survey analysis for the neighborhood market managers is the demographics they should target for this model. From the cross analysis, it was very evident that the population segment least likely to utilize the veggie box model at the neighborhood markets were those individuals with a college degree or higher who also have a car. This demographic shopped at grocery stores and wanted to continue shopping at grocery stores, even if neighborhood markets did adopt the veggie box model. Rather, neighborhood market managers should focus on customers that have a longer commute to a grocery store and shop less frequently. Unsurprisingly, this is the segment of the population most affected by living in food deserts – individuals who live furthest from a grocery store and might have the most difficulty getting to fresh produce.

The next task for the neighborhood market managers will be to get these individuals to increase their shopping frequency. This is important because the veggie box model is most effective when there is a subscription service. The barrier to this model for customers who shop infrequently would be getting them to shop more often so they can continuously pick up their subscribed produce items. This might mean more advertising for corner store managers and explaining the benefits of the veggie box model to the customers. This might be a bit easier, because one of the benefits of neighborhood markets is their strong relationship with the community. As such, they might be able to build a better relationship with these new customers and be better positioned to shift their shopping habits.



### **5.3.2 Managerial Insights from Interviews**

It is extremely important for neighborhood market managers to have a relationship with both their customers as well as their suppliers if they were interested in utilizing the veggie box model. For the customers, they would need to have a grasp on the types of produce that customers are most interested in, the frequency of deliveries, and the times in which customers could pick up their items. The produce preferences are important to ensure that customers begin a subscription, they will keep it long enough for the neighborhood market to sustain a profit. The frequency of deliveries and time of pick up is important because the neighborhood market inventory space has a potential to be a big concern. Market managers will have to be very deliberate about the number of subscriptions they can offer, given the inventory pace they have available. They can optimize this number by requesting each customer picks up their delivery on certain days of the week. This way they can ensure that they have enough space for their other customers on other days.

On the supplier side, since the neighborhood markets have relatively small capacity, they will have difficulty purchasing from large scale wholesalers or large-scale farmers. Thus, they will need to source from smaller farms. Therefore, the neighborhood market managers will have to ensure that the produce from these small-scale farmers is reliable and consistent. They may need to source from a few different suppliers to ensure there is enough variety to meet their customers' needs, since many of the individual farmers will be limited in the scope of products they can grow. To supplement distribution from the farmers, another option is to form a buying group with other neighborhood markets in the city and "bulk buy" produce from a wholesaler. This might be a feasible option because the biggest barrier for wholesalers selling to neighborhood markets is volume. If a conglomerate of corner stores teams up and make on big purchase of the wholesaler, then divvy up the produce upon purchase, this could bring wholesalers back into the supply chain

for the veggie box. This option does add some complexity to the neighborhood markets' supply chain. It requires trusting other stores (who could be seen as competitors), and finding a fair way to divide the produce that is received from the wholesalers.

## **6. CONCLUSIONS AND FUTURE WORK**

This capstone research project sought to answer two research questions in regards to sourcing food desert communities with healthy food options:

- 1) What food supply chain model (grocery delivery, rideshare, veggie-box) would residents of low-income areas prefer?
- 2) What is the feasibility of implementing this food supply chain model to increase healthy foods in low-income areas?

In conclusion, the research found that 1) The veggie box model is the preferred method for receiving fresh vegetables in food-deserts for residents of Somerville, MA and 2) this is a feasible and cost-effective solution, when considering the needs of each of the stakeholders in the supply chain.

### **6.1 Limitations of Our Work**

While the researchers were able to answer the research questions posed, there are few limitations to the research presented in this paper.

#### **6.1.1 Survey Collection**

First, the sampling for the surveys in this paper were not ideal. Of all the surveys collected, 30% of them came from senior homes and shelters, while the other 70% came from people shopping at larger supermarkets like Stop and Shop, Star Market, and Market Basket. They were not collected at actual neighborhood markets, which places bias in the pool that was sampled.

### **6.1.2 Interviews**

Only one interview was collected to represent the perspective of distributors/wholesalers. This is a major hinderance to the research at hand. It was particularly difficult to get in contact with distributors for this project. Many of them were hard to reach and of those who were contacted, most were not interested in responding to the interview. This means that this research may not have been indicative of all or even a majority of distributors/wholesalers. It is imperative to gain a better understanding of how the distributors operate in order to improve this work.

## **6.2 Future Research**

### **6.2.1 Data Analysis**

In this analysis of the data, the researchers utilized a descriptive analysis, cross-validation analysis, principal component analysis, and a logistic regression model to analyze the data. In further research, the researchers recommend utilizing a cluster analysis for consumer profiles. This is another means of gathering like behaviors for customers together and seeing what factors make them alike. These clusters could then be used to perform a multi-level structural equation model and an explanatory factor analysis. These two additional steps would allow researchers to study if each factor is a moderating variable (one that affects the *strength* of the relationship between the independent and dependent variables) or mediating variable (one that explains the *nature* of the relationship between the independent and dependent variable). For example, a person's proximity to a grocery store might be a mediating variable and their accessibility to SNAP might be a moderating variable.

Lastly, further research might conduct a conjoint analysis of the data. This analysis gives the likelihood that a respondent would select a particular option, if they were given a choice between two options. For example, it could indicate that women under 50, who live more than ten

minutes away from a grocery store are more likely to choose the veggie box model. This analysis would give further insight into customer preferences and could aid in answering the research question in more nuanced ways.

### **6.2.2 Survey Collection**

For future research, many more surveys should be collected at actual neighborhood markets to ensure a more balanced number of respondents. Also, there should be a better mechanism of ensuring those who responded to the surveys actually lived in food desert communities. This would ensure the data being analyzed serves the population that the researchers intend.

Another area where this study could be improved in subsequent research is the location where the research was conducted. While Somerville does have a few small pockets of low-income individuals and also has several food-deserts within the city, the city is pretty wealthy overall. Even among those surveyed, 61.65% of respondents had a master's degree or higher and a total of 92.1% had a college degree or higher. Although individual income was not asked in the survey, a good proxy for income in the United States has been education attainment. This data seems to include individuals on the higher end of that spectrum. In fact, the median income in Somerville, according to 2018 ACS Census data, is \$91,000. This is much higher than the US average. A recommendation for future research would be to target areas that have a much lower median income. Somerville would not be considered an "under resourced" city, like those where many food-deserts across the United States appear. The city of Somerville does have an approximate 12% poverty level however, since this project did not ask for income level in the survey there was no control for contacting just this segment of the city.

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## APPENDICES

### APPENDIX 1 – SURVEY

The survey applied with the residents of Somerville-MA is available on this link: [https://mit.co1.qualtrics.com/jfe/form/SV\\_9SmbBnhJXfz5165](https://mit.co1.qualtrics.com/jfe/form/SV_9SmbBnhJXfz5165)

### APPENDIX 2 – LIST OF QUESTIONS

For Distributors and Wholesalers:

1. What are the products you manage? Why?
2. What is your logistics capacity (vehicles, equipment, space in facilities, staff)?
3. Which farms/farmers and retailers do you work with?
  - a. What type of agreements/partnerships do you have with them?
  - b. Do they have similar features, respectively?
4. What does your demand for Fruits and Vegetables look like?
  - a. What does your customers' demand for fruits and vegetables demand look like?
5. What do your logistic operations (e.g. picking, packing, transportation, warehousing) look like?
6. What is your plan for the near future and in general?
  - a. How do you plan to grow the number of stakeholders and your capacity?
  - b. Why?
7. If you haven't been supplying to low-income communities, are you interested in working with them?
  - a. What are your concerns (no/yes but not put into action)?
  - b. Would you consider supplying to low-income communities if there were subsidies or other assistance (no/yes but not put into action)?
  - c. Why?

For Farmers and Farmer Associations:

1. Which individual farms/farmers have you worked with? What do they offer (e.g. fruits and vegetables, dairy, meat and poultry, etc.)?
2. Besides farms/farms, what other parties do you reach out to or have worked with?
  - a. What external connections do you have?
3. How do you finance the operations?
  - a. Do farms need to pay for membership, events, etc.?
4. Have you considered/Will you consider connecting farms/farmers with the end consumers directly?  
Why?
  - a. What are your concerns and/or obstacles (no/yes but not put into action)?
5. What is your plan for the near future and in general?
  - a. How do you plan to grow the number of farms/farmers? Why?
6. What are the size requirements you ask of farmers to be part of this association?
7. What do your logistic operations (e.g. picking, packing, transportation, warehousing) look like?
8. Do you own, lease vehicles, equipment, facilities, staff for the individual farms/farmers?
9. Do you have a minimum order quantity for your customers?

## APPENDIX 3 – LIST OF VARIABLES

Survey Question	Variable Code	Category	Subcategory
Q24	DV1	Ridesharing	Ridesharing
Q24	DV2	Grocery Delivery	Grocery Delivery
Q26	DV3	Veggie Box	Veggie Box
Q4	IV1	Frequency of Shopping	Grocery Stores
Q4	IV2	Frequency of Shopping	Neighborhood Markets
Q4	IV3	Frequency of Shopping	Other Places
Q5	IV4	Quantity of Groceries	Neighborhood Markets
Q8	IV5	Location of Grocery Shopping	Farmers Market
Q8	IV6	Location of Grocery Shopping	Grocery Stores
Q8	IV7	Location of Grocery Shopping	Grocery Store and Farmers Market
Q8	IV8	Location of Grocery Shopping	Grocery Store and Neighborhood Market
Q8	IV9	Location of Grocery Shopping	Grocery Store, Neighborhood Market and Farmers Market
Q8	IV10	Location of Grocery Shopping	Neighborhood Market
Q8	IV11	Location of Grocery Shopping	Neighborhood Market and Farmers Market
Q8	IV12	Location of Grocery Shopping	Other
Q10	IV13	Method of Transportation to a Grocery Store	Walk
Q10	IV14	Method of Transportation to a Grocery Store	Walk and Public Transportation
Q10	IV15	Method of Transportation to a Grocery Store	Walk, Public Transportation, and Ridesharing
Q10	IV16	Method of Transportation to a Grocery Store	Walk, Public Transp., Ridesharing, and Vehicle
Q10	IV17	Method of Transportation to a Grocery Store	Walk, Public Transp., and Vehicle
Q10	IV18	Method of Transportation to a Grocery Store	Walk and Vehicle
Q10	IV19	Method of Transportation to a Grocery Store	Walk, Ridesharing, and Vehicle
Q10	IV20	Method of Transportation to a Grocery Store	Public Transportation
Q10	IV21	Method of Transportation to a Grocery Store	Public Transp., Ridesharing, and Vehicle
Q10	IV22	Method of Transportation to a Grocery Store	Public Transp. and Vehicle
Q10	IV23	Method of Transportation to a Grocery Store	Vehicle
Q10	IV24	Method of Transportation to a Grocery Store	Ridesharing, and Vehicle
Q10	IV25	Method of Transportation to a Grocery Store	Walk, Car, and Other
Q11	IV26	Travel Time	To a Store
Q12	IV27	Method of Transportation from a Grocery Store	Walk
Q12	IV28	Method of Transportation from a Grocery Store	Walk and Public Transportation
Q12	IV29	Method of Transportation from a Grocery Store	Walk, Public Transportation, and Ridesharing
Q12	IV30	Method of Transportation from a Grocery Store	Walk, Public Transp., Ridesharing, and Vehicle
Q12	IV31	Method of Transportation from a Grocery Store	Walk, Public Transp., and Vehicle
Q12	IV32	Method of Transportation from a Grocery Store	Walk and Ridesharing
Q12	IV33	Method of Transportation from a Grocery Store	Walk, Ridesharing, and Vehicle
Q12	IV34	Method of Transportation from a Grocery Store	Walk and Vehicle
Q12	IV35	Method of Transportation from a Grocery Store	Walk, Ridesharing, and Vehicle
Q12	IV36	Method of Transportation from a Grocery Store	Public Transportation
Q12	IV37	Method of Transportation from a Grocery Store	Public Transp. and Vehicle
Q12	IV38	Method of Transportation from a Grocery Store	Ridesharing
Q12	IV39	Method of Transportation from a Grocery Store	Ridesharing, Vehicle, and Other
Q12	IV40	Method of Transportation from a Grocery Store	Vehicle
Q12	IV41	Method of Transportation from a Grocery Store	Ridesharing, and Vehicle
Q12	IV42	Method of Transportation from a Grocery Store	Walk, Car, and Other
Q13	IV43	Travel Time	From a Store
Q15	IV44	Effects from Method of Transportation	Quantity of Food Purchased
Q15	IV45	Effects from Method of Transportation	Type of Food Purchased
Q16	IV46	Ideal Transportation Method to a Store	Satisfied with current situation
Q16	IV47	Ideal Transportation Method to a Store	Walk and/or Bike
Q16	IV48	Ideal Transportation Method to a Store	Public Transportation
Q16	IV49	Ideal Transportation Method to a Store	Ridesharing
Q16	IV50	Ideal Transportation Method to a Store	Vehicle
Q18	IV51	Household Car	Household Car
Q19	IV52	Smartphone	Smartphone
Q20	IV53	Comfortable in using Rideshare Apps	Comfortable in using Rideshare Apps
Q21	IV54	Use of Ridesharing	Use of Ridesharing
Q22	IV55	Use of Grocery Delivery	Use of Grocery Delivery
Q28	IV56	Comfortable with someone else selecting the F&V	Comfortable with someone else selecting the F&V
Q28	IV57	Household Meals Adaptation to Veggie Box	Household Meals Adaptation to Veggie Box
Q31	IV58	Weekly Grocery Spent	\$100-150
Q31	IV59	Weekly Grocery Spent	\$150-200
Q31	IV60	Weekly Grocery Spent	\$200-250
Q31	IV61	Weekly Grocery Spent	\$250-300
Q31	IV62	Weekly Grocery Spent	Less than \$100
Q33	IV63	Food Run Out	Q33_1
Q33	IV64	Food Not Enough and No Money	Q33_2
Q36	IV65	Number of People for Shopping Groceries	0-5 years old
Q36	IV66	Number of People for Shopping Groceries	6 - 18 years old
Q36	IV67	Number of People for Shopping Groceries	19 - 60 years old
Q36	IV68	Number of People for Shopping Groceries	Over 60 years old
Q39	IV69	Age	Age
Q38	IV70	Gender	Gender
Q40	IV71	Educational Level	Educational Level
Q41	IV72	Race	Race

**APPENDIX 4 – IV1, IV43, AND LOW-COST RIDESHARING MODEL**

RSharingDV			IV43					Total	
			.00	1.00	2.00	3.00	4.00		
.00	IV1	.00	Count	9	9	1		0	19
			% within IV1	47.4%	47.4%	5.3%		0.0%	100.0%
			% within IV43	8.2%	13.0%	11.1%		0.0%	10.1%
			% of Total	4.8%	4.8%	0.5%		0.0%	10.1%
1.00			Count	0	1	0		0	1
			% within IV1	0.0%	100.0%	0.0%		0.0%	100.0%
			% within IV43	0.0%	1.4%	0.0%		0.0%	0.5%
			% of Total	0.0%	0.5%	0.0%		0.0%	0.5%
2.00			Count	2	1	1		0	4
			% within IV1	50.0%	25.0%	25.0%		0.0%	100.0%
			% within IV43	1.8%	1.4%	11.1%		0.0%	2.1%
			% of Total	1.1%	0.5%	0.5%		0.0%	2.1%
3.00			Count	3	2	1		0	6
			% within IV1	50.0%	33.3%	16.7%		0.0%	100.0%
			% within IV43	2.7%	2.9%	11.1%		0.0%	3.2%
			% of Total	1.6%	1.1%	0.5%		0.0%	3.2%
4.00			Count	12	6	0		1	19
			% within IV1	63.2%	31.6%	0.0%		5.3%	100.0%
			% within IV43	10.9%	8.7%	0.0%		100.0%	10.1%
			% of Total	6.3%	3.2%	0.0%		0.5%	10.1%
5.00			Count	49	31	3		0	83
			% within IV1	59.0%	37.3%	3.6%		0.0%	100.0%
			% within IV43	44.5%	44.9%	33.3%		0.0%	43.9%
			% of Total	25.9%	16.4%	1.6%		0.0%	43.9%
6.00			Count	34	19	3		0	56
			% within IV1	60.7%	33.9%	5.4%		0.0%	100.0%
			% within IV43	30.9%	27.5%	33.3%		0.0%	29.6%

			% of Total	18.0%	10.1%	1.6%		0.0%	29.6%
	7.00		Count	1	0	0		0	1
			% within IV1	100.0%	0.0%	0.0%		0.0%	100.0%
			% within IV43	0.9%	0.0%	0.0%		0.0%	0.5%
			% of Total	0.5%	0.0%	0.0%		0.0%	0.5%
	Total		Count	110	69	9		1	189
			% within IV1	58.2%	36.5%	4.8%		0.5%	100.0%
			% within IV43	100.0%	100.0%	100.0%		100.0%	100.0%
			% of Total	58.2%	36.5%	4.8%		0.5%	100.0%
1.00	IV1	.00	Count	4	8	3	1	0	16
			% within IV1	25.0%	50.0%	18.8%	6.3%	0.0%	100.0%
			% within IV43	16.7%	22.9%	27.3%	50.0%	0.0%	20.8%
			% of Total	5.2%	10.4%	3.9%	1.3%	0.0%	20.8%
	2.00		Count	0	1	0	0	0	1
			% within IV1	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	0.0%	2.9%	0.0%	0.0%	0.0%	1.3%
			% of Total	0.0%	1.3%	0.0%	0.0%	0.0%	1.3%
	3.00		Count	0	1	1	1	0	3
			% within IV1	0.0%	33.3%	33.3%	33.3%	0.0%	100.0%
			% within IV43	0.0%	2.9%	9.1%	50.0%	0.0%	3.9%
			% of Total	0.0%	1.3%	1.3%	1.3%	0.0%	3.9%
	4.00		Count	4	8	1	0	0	13
			% within IV1	30.8%	61.5%	7.7%	0.0%	0.0%	100.0%
			% within IV43	16.7%	22.9%	9.1%	0.0%	0.0%	16.9%
			% of Total	5.2%	10.4%	1.3%	0.0%	0.0%	16.9%
	5.00		Count	11	9	2	0	3	25
			% within IV1	44.0%	36.0%	8.0%	0.0%	12.0%	100.0%
			% within IV43	45.8%	25.7%	18.2%	0.0%	60.0%	32.5%
			% of Total	14.3%	11.7%	2.6%	0.0%	3.9%	32.5%
	6.00		Count	5	7	4	0	1	17

	% within IV1	29.4%	41.2%	23.5%	0.0%	5.9%	100.0%
	% within IV43	20.8%	20.0%	36.4%	0.0%	20.0%	22.1%
	% of Total	6.5%	9.1%	5.2%	0.0%	1.3%	22.1%
7.00	Count	0	1	0	0	1	2
	% within IV1	0.0%	50.0%	0.0%	0.0%	50.0%	100.0%
	% within IV43	0.0%	2.9%	0.0%	0.0%	20.0%	2.6%
	% of Total	0.0%	1.3%	0.0%	0.0%	1.3%	2.6%
Total	Count	24	35	11	2	5	77
	% within IV1	31.2%	45.5%	14.3%	2.6%	6.5%	100.0%
	% within IV43	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	% of Total	31.2%	45.5%	14.3%	2.6%	6.5%	100.0%

**APPENDIX 5 – IV1, IV43, AND LOW-COST DELIVERY MODEL**

Low-Cost Delivery Model			IV43					Total	
.00	IV1	.00	.00	1.00	2.00	3.00	4.00		
			Count	4	4	1	0	0	9
			% within IV1	44.4%	44.4%	11.1%	0.0%	0.0%	100.0%
			% within IV43	5.3%	7.0%	9.1%	0.0%	0.0%	6.1%
			% of Total	2.7%	2.7%	0.7%	0.0%	0.0%	6.1%
	1.00		Count	2	1	0	0	0	3
			% within IV1	66.7%	33.3%	0.0%	0.0%	0.0%	100.0%
			% within IV43	2.7%	1.8%	0.0%	0.0%	0.0%	2.0%
			% of Total	1.4%	0.7%	0.0%	0.0%	0.0%	2.0%
	2.00		Count	1	1	1	1	0	4
			% within IV1	25.0%	25.0%	25.0%	25.0%	0.0%	100.0%
			% within IV43	1.3%	1.8%	9.1%	100.0%	0.0%	2.7%
			% of Total	0.7%	0.7%	0.7%	0.7%	0.0%	2.7%
	3.00		Count	12	5	1	0	1	19
			% within IV1	63.2%	26.3%	5.3%	0.0%	5.3%	100.0%
			% within IV43	16.0%	8.8%	9.1%	0.0%	33.3%	12.9%
			% of Total	8.2%	3.4%	0.7%	0.0%	0.7%	12.9%
	4.00		Count	33	26	2	0	2	63
			% within IV1	52.4%	41.3%	3.2%	0.0%	3.2%	100.0%
			% within IV43	44.0%	45.6%	18.2%	0.0%	66.7%	42.9%
			% of Total	22.4%	17.7%	1.4%	0.0%	1.4%	42.9%
	5.00		Count	22	20	6	0	0	48
			% within IV1	45.8%	41.7%	12.5%	0.0%	0.0%	100.0%
			% within IV43	29.3%	35.1%	54.5%	0.0%	0.0%	32.7%
			% of Total	15.0%	13.6%	4.1%	0.0%	0.0%	32.7%
	6.00		Count	1	0	0	0	0	1
			% within IV1	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	1.3%	0.0%	0.0%	0.0%	0.0%	0.7%



			% of Total	0.7%	0.0%	0.0%	0.0%	0.0%	0.7%
	7.00		Count	75	57	11	1	3	147
			% within IV1	51.0%	38.8%	7.5%	0.7%	2.0%	100.0%
			% within IV43	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
			% of Total	51.0%	38.8%	7.5%	0.7%	2.0%	100.0%
	Total		Count	110	9	13	3	1	0
			% within IV1	58.2%	34.6%	50.0%	11.5%	3.8%	0.0%
			% within IV43	100.0%	15.3%	27.7%	33.3%	100.0%	0.0%
			% of Total	58.2%	7.6%	10.9%	2.5%	0.8%	0.0%
1.00	IV1	.00	Count	0	1	0	0	0	1
			% within IV1	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	0.0%	2.1%	0.0%	0.0%	0.0%	0.8%
			% of Total	0.0%	0.8%	0.0%	0.0%	0.0%	0.8%
	2.00		Count	0	1	1	0	0	2
			% within IV1	0.0%	50.0%	50.0%	0.0%	0.0%	100.0%
			% within IV43	0.0%	2.1%	11.1%	0.0%	0.0%	1.7%
			% of Total	0.0%	0.8%	0.8%	0.0%	0.0%	1.7%
	3.00		Count	2	2	1	0	0	5
			% within IV1	40.0%	40.0%	20.0%	0.0%	0.0%	100.0%
			% within IV43	3.4%	4.3%	11.1%	0.0%	0.0%	4.2%
			% of Total	1.7%	1.7%	0.8%	0.0%	0.0%	4.2%
	4.00		Count	4	9	0	0	0	13
			% within IV1	30.8%	69.2%	0.0%	0.0%	0.0%	100.0%
			% within IV43	6.8%	19.1%	0.0%	0.0%	0.0%	10.9%
			% of Total	3.4%	7.6%	0.0%	0.0%	0.0%	10.9%
	5.00		Count	27	14	3	0	1	45
			% within IV1	60.0%	31.1%	6.7%	0.0%	2.2%	100.0%
			% within IV43	45.8%	29.8%	33.3%	0.0%	33.3%	37.8%
			% of Total	22.7%	11.8%	2.5%	0.0%	0.8%	37.8%
	6.00		Count	17	6	1	0	1	25

	% within IV1	68.0%	24.0%	4.0%	0.0%	4.0%	100.0%
	% within IV43	28.8%	12.8%	11.1%	0.0%	33.3%	21.0%
	% of Total	14.3%	5.0%	0.8%	0.0%	0.8%	21.0%
7.00	Count	0	1	0	0	1	2
	% within IV1	0.0%	50.0%	0.0%	0.0%	50.0%	100.0%
	% within IV43	0.0%	2.1%	0.0%	0.0%	33.3%	1.7%
	% of Total	0.0%	0.8%	0.0%	0.0%	0.8%	1.7%
Total	Count	24	59	47	9	1	3
	% within IV1	31.2%	49.6%	39.5%	7.6%	0.8%	2.5%
	% within IV43	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	% of Total	31.2%	49.6%	39.5%	7.6%	0.8%	2.5%

**APPENDIX 6 – IV1, IV43, AND VEGGIE BOX MODEL**

Veggie Box Model			IV43					Total	
.00	IV1	.00	.00	1.00	2.00	3.00	4.00		
			Count	3	0	0	0	0	3
			% within IV1	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	12.5%	0.0%	0.0%	0.0%	0.0%	7.3%
			% of Total	7.3%	0.0%	0.0%	0.0%	0.0%	7.3%
	1.00		Count	0	1	0	0	0	1
			% within IV1	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	0.0%	8.3%	0.0%	0.0%	0.0%	2.4%
			% of Total	0.0%	2.4%	0.0%	0.0%	0.0%	2.4%
	2.00		Count	0	1	0	1	0	2
			% within IV1	0.0%	50.0%	0.0%	50.0%	0.0%	100.0%
			% within IV43	0.0%	8.3%	0.0%	100.0%	0.0%	4.9%
			% of Total	0.0%	2.4%	0.0%	2.4%	0.0%	4.9%
	3.00		Count	4	1	0	0	1	6
			% within IV1	66.7%	16.7%	0.0%	0.0%	16.7%	100.0%
			% within IV43	16.7%	8.3%	0.0%	0.0%	33.3%	14.6%
			% of Total	9.8%	2.4%	0.0%	0.0%	2.4%	14.6%
	4.00		Count	8	4	0	0	2	14
			% within IV1	57.1%	28.6%	0.0%	0.0%	14.3%	100.0%
			% within IV43	33.3%	33.3%	0.0%	0.0%	66.7%	34.1%
			% of Total	19.5%	9.8%	0.0%	0.0%	4.9%	34.1%
	5.00		Count	8	5	1	0	0	14
			% within IV1	57.1%	35.7%	7.1%	0.0%	0.0%	100.0%
			% within IV43	33.3%	41.7%	100.0%	0.0%	0.0%	34.1%
			% of Total	19.5%	12.2%	2.4%	0.0%	0.0%	34.1%
	6.00		Count	1	0	0	0	0	1
			% within IV1	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
			% within IV43	4.2%	0.0%	0.0%	0.0%	0.0%	2.4%

			% of Total	2.4%	0.0%	0.0%	0.0%	0.0%	2.4%
	7.00		Count	24	12	1	1	3	41
			% within IV1	58.5%	29.3%	2.4%	2.4%	7.3%	100.0%
			% within IV43	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
			% of Total	58.5%	29.3%	2.4%	2.4%	7.3%	100.0%
	Total		Count	110	10	17	4	1	0
			% within IV1	58.2%	31.3%	53.1%	12.5%	3.1%	0.0%
			% within IV43	100.0%	9.1%	18.5%	21.1%	100.0%	0.0%
			% of Total	58.2%	4.4%	7.6%	1.8%	0.4%	0.0%
1.00	IV1	.00	Count	2	2	1	0	0	5
			% within IV1	40.0%	40.0%	20.0%	0.0%	0.0%	100.0%
			% within IV43	1.8%	2.2%	5.3%	0.0%	0.0%	2.2%
			% of Total	0.9%	0.9%	0.4%	0.0%	0.0%	2.2%
	2.00		Count	3	2	2	0	0	7
			% within IV1	42.9%	28.6%	28.6%	0.0%	0.0%	100.0%
			% within IV43	2.7%	2.2%	10.5%	0.0%	0.0%	3.1%
			% of Total	1.3%	0.9%	0.9%	0.0%	0.0%	3.1%
	3.00		Count	12	13	1	0	0	26
			% within IV1	46.2%	50.0%	3.8%	0.0%	0.0%	100.0%
			% within IV43	10.9%	14.1%	5.3%	0.0%	0.0%	11.6%
			% of Total	5.3%	5.8%	0.4%	0.0%	0.0%	11.6%
	4.00		Count	52	36	5	0	1	94
			% within IV1	55.3%	38.3%	5.3%	0.0%	1.1%	100.0%
			% within IV43	47.3%	39.1%	26.3%	0.0%	33.3%	41.8%
			% of Total	23.1%	16.0%	2.2%	0.0%	0.4%	41.8%
	5.00		Count	31	21	6	0	1	59
			% within IV1	52.5%	35.6%	10.2%	0.0%	1.7%	100.0%
			% within IV43	28.2%	22.8%	31.6%	0.0%	33.3%	26.2%
			% of Total	13.8%	9.3%	2.7%	0.0%	0.4%	26.2%
	6.00		Count	0	1	0	0	1	2

	% within IV1	0.0%	50.0%	0.0%	0.0%	50.0%	100.0%
	% within IV43	0.0%	1.1%	0.0%	0.0%	33.3%	0.9%
	% of Total	0.0%	0.4%	0.0%	0.0%	0.4%	0.9%
7.00	Count	110	92	19	1	3	225
	% within IV1	48.9%	40.9%	8.4%	0.4%	1.3%	100.0%
	% within IV43	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	% of Total	48.9%	40.9%	8.4%	0.4%	1.3%	100.0%
Total	Count	24	3	0	0	0	0
	% within IV1	31.2%	100.0%	0.0%	0.0%	0.0%	0.0%
	% within IV43	100.0%	12.5%	0.0%	0.0%	0.0%	0.0%
	% of Total	31.2%	7.3%	0.0%	0.0%	0.0%	0.0%

**APPENDIX 7 – EDUCATIONAL LEVEL, CAR OWNERSHIP, AND USE OF RIDESHARING**

			IV51		Total	
IV54			.00	1.00		
.00	IV71	2.00	Count	1	0	1
			% within IV71	100.0%	0.0%	100.0%
			% within IV51	12.5%	0.0%	2.4%
			% of Total	2.4%	0.0%	2.4%
		3.00	Count	0	2	2
		% within IV71	0.0%	100.0%	100.0%	
		% within IV51	0.0%	6.1%	4.9%	
		% of Total	0.0%	4.9%	4.9%	
		4.00	Count	5	8	13
		% within IV71	38.5%	61.5%	100.0%	
		% within IV51	62.5%	24.2%	31.7%	
		% of Total	12.2%	19.5%	31.7%	
		5.00	Count	2	23	25
		% within IV71	8.0%	92.0%	100.0%	
		% within IV51	25.0%	69.7%	61.0%	
		% of Total	4.9%	56.1%	61.0%	
	Total	Count	8	33	41	
		% within IV71	19.5%	80.5%	100.0%	
		% within IV51	100.0%	100.0%	100.0%	
		% of Total	19.5%	80.5%	100.0%	
1.00	IV71	1.00	Count	0	1	1
			% within IV71	0.0%	100.0%	100.0%
			% within IV51	0.0%	0.6%	0.4%
			% of Total	0.0%	0.4%	0.4%
		2.00	Count	1	5	6
		% within IV71	16.7%	83.3%	100.0%	

			% within IV51	1.9%	2.9%	2.7%
			% of Total	0.4%	2.2%	2.7%
		3.00	Count	4	7	11
			% within IV71	36.4%	63.6%	100.0%
			% within IV51	7.7%	4.0%	4.9%
			% of Total	1.8%	3.1%	4.9%
		4.00	Count	25	43	68
			% within IV71	36.8%	63.2%	100.0%
			% within IV51	48.1%	24.9%	30.2%
			% of Total	11.1%	19.1%	30.2%
		5.00	Count	22	117	139
			% within IV71	15.8%	84.2%	100.0%
			% within IV51	42.3%	67.6%	61.8%
			% of Total	9.8%	52.0%	61.8%
		Total	Count	52	173	225
			% within IV71	23.1%	76.9%	100.0%
			% within IV51	100.0%	100.0%	100.0%
			% of Total	23.1%	76.9%	100.0%
Total	IV71	1.00	Count	0	1	1
			% within IV71	0.0%	100.0%	100.0%
			% within IV51	0.0%	0.5%	0.4%
			% of Total	0.0%	0.4%	0.4%
		2.00	Count	2	5	7
			% within IV71	28.6%	71.4%	100.0%
			% within IV51	3.3%	2.4%	2.6%
			% of Total	0.8%	1.9%	2.6%
		3.00	Count	4	9	13
			% within IV71	30.8%	69.2%	100.0%
			% within IV51	6.7%	4.4%	4.9%
			% of Total	1.5%	3.4%	4.9%

4.00	Count	30	51	81
	% within IV71	37.0%	63.0%	100.0%
	% within IV51	50.0%	24.8%	30.5%
	% of Total	11.3%	19.2%	30.5%
5.00	Count	24	140	164
	% within IV71	14.6%	85.4%	100.0%
	% within IV51	40.0%	68.0%	61.7%
	% of Total	9.0%	52.6%	61.7%
Total	Count	60	206	266
	% within IV71	22.6%	77.4%	100.0%
	% within IV51	100.0%	100.0%	100.0%
	% of Total	22.6%	77.4%	100.0%



## APPENDIX 8 – CORRELATION MATRIX

	IV1	IV2	IV3	IV4	IV5	IV6	IV7	IV8	IV9	IV10	IV11	IV12	IV13	IV14	IV15	IV16	IV17	IV18	IV19	IV20	IV21	IV22	IV23
IV1	1.000	0.083	0.159	-0.148	0.000	0.162	0.029	-0.176	-0.012	-0.195	-0.083	0.009	0.053	-0.050	-0.040	-0.099	0.057	-0.050	-0.140	-0.017	0.028	0.020	0.083
IV2	0.083	1.000	0.251	0.429	0.015	-0.206	-0.025	0.106	0.155	-0.010	0.285	-0.001	0.128	-0.007	-0.051	-0.066	0.015	0.034	0.005	-0.091	-0.066	-0.064	-0.076
IV3	0.159	0.251	1.000	-0.083	-0.011	0.070	-0.010	-0.017	-0.023	-0.121	0.026	-0.006	0.041	0.006	0.018	-0.028	-0.025	-0.023	0.087	-0.094	0.096	-0.066	0.016
IV4	-0.148	0.429	-0.083	1.000	0.023	-0.288	-0.088	0.063	0.213	0.339	0.408	-0.120	0.106	0.050	-0.015	-0.031	0.080	-0.007	0.018	0.026	-0.031	0.018	-0.155
IV5	0.000	0.015	-0.011	0.023	1.000	-0.180	-0.095	-0.049	-0.054	-0.031	-0.027	-0.027	0.026	-0.052	-0.019	-0.024	-0.031	0.014	-0.011	0.239	-0.015	-0.011	-0.017
IV6	0.162	-0.206	0.070	-0.288	-0.180	1.000	-0.552	-0.284	-0.315	-0.180	-0.155	-0.155	-0.021	0.035	0.033	0.025	0.040	-0.127	-0.063	-0.002	-0.002	0.060	0.118
IV7	0.029	-0.025	-0.010	-0.088	-0.095	-0.552	1.000	-0.150	-0.166	-0.095	-0.082	-0.082	0.057	-0.058	-0.058	-0.075	-0.042	0.070	0.114	-0.047	0.057	-0.033	-0.031
IV8	-0.176	0.106	-0.017	0.063	-0.049	-0.284	-0.150	1.000	-0.085	-0.049	-0.042	-0.042	-0.098	0.027	0.109	0.069	-0.049	0.110	-0.017	-0.024	-0.024	-0.017	-0.050
IV9	-0.012	0.155	-0.023	0.213	-0.054	-0.315	-0.166	-0.085	1.000	-0.054	-0.047	-0.047	-0.048	0.059	-0.033	0.056	0.024	0.034	-0.019	-0.027	-0.027	-0.019	-0.022
IV10	-0.195	-0.010	-0.121	0.339	-0.031	-0.180	-0.095	-0.049	-0.054	1.000	-0.027	-0.027	-0.030	0.030	-0.019	-0.024	0.098	0.014	-0.011	-0.015	-0.015	-0.011	-0.065
IV11	-0.083	0.285	0.026	0.408	-0.027	-0.155	-0.082	-0.042	-0.047	-0.027	1.000	-0.023	0.183	-0.044	-0.016	-0.021	-0.027	-0.002	-0.009	-0.013	-0.013	-0.009	-0.098
IV12	0.009	-0.001	-0.006	-0.120	-0.027	-0.155	-0.082	-0.042	-0.047	-0.027	-0.023	1.000	-0.010	-0.044	-0.016	-0.021	-0.027	-0.055	-0.009	-0.013	-0.013	-0.009	0.013
IV13	0.053	0.128	0.041	0.106	0.026	-0.021	0.057	-0.098	-0.048	-0.030	0.183	-0.010	1.000	-0.143	-0.052	-0.067	-0.086	-0.348	-0.030	-0.042	-0.042	-0.030	-0.314
IV14	-0.050	-0.007	0.006	0.050	-0.052	0.035	-0.058	0.027	0.059	0.030	-0.044	-0.044	-0.314	1.000	-0.031	-0.041	-0.052	-0.209	-0.018	-0.025	-0.025	-0.018	-1.889
IV15	-0.040	-0.051	0.018	-0.015	-0.019	0.033	-0.058	0.109	-0.033	-0.019	-0.016	-0.016	-0.052	-0.031	1.000	-0.015	-0.019	-0.076	-0.007	-0.009	-0.009	-0.007	-0.069
IV16	-0.099	-0.066	-0.028	-0.031	-0.024	0.025	-0.075	0.069	0.056	-0.024	-0.021	-0.021	-0.067	-0.041	-0.015	1.000	-0.024	-0.099	-0.009	-0.012	-0.012	-0.009	-0.089
IV17	0.057	0.015	-0.025	0.080	-0.031	0.040	-0.042	-0.049	0.024	0.098	-0.027	-0.027	-0.086	-0.052	-0.019	-0.024	1.000	-0.110	-0.011	-0.015	-0.015	-0.011	-1.113
IV18	-0.050	0.034	-0.023	-0.007	0.014	-0.127	0.070	0.110	0.034	0.014	-0.002	-0.055	-0.348	-0.209	-0.076	-0.099	-0.126	1.000	-0.044	-0.062	-0.062	-0.044	-0.461
IV19	-0.140	0.005	0.087	0.018	-0.011	-0.063	0.114	-0.017	-0.019	-0.011	-0.009	-0.009	-0.030	-0.018	-0.007	-0.009	-0.011	-0.044	1.000	-0.005	-0.005	-0.004	-0.040
IV20	-0.017	-0.091	-0.094	0.026	0.239	-0.002	-0.047	-0.024	-0.027	-0.015	-0.013	-0.013	-0.042	-0.025	-0.009	-0.012	-0.012	-0.002	-0.009	-0.013	-0.013	-0.009	-0.056
IV21	0.028	-0.066	0.096	-0.031	-0.015	-0.002	0.057	-0.024	-0.027	-0.015	-0.013	-0.013	-0.042	-0.025	-0.009	-0.012	-0.015	-0.062	-0.005	-0.008	1.000	-0.005	-0.056
IV22	0.020	-0.064	-0.066	0.018	-0.011	0.060	-0.033	-0.017	-0.019	-0.011	-0.009	-0.009	-0.030	-0.018	-0.007	-0.009	-0.011	-0.044	-0.004	-0.005	-0.005	1.000	-0.040
IV23	0.083	-0.076	0.016	-0.155	-0.017	0.118	-0.031	-0.050	-0.022	-0.065	-0.098	0.013	-0.314	-0.189	-0.069	-0.089	-0.113	-0.461	-0.040	-0.056	-0.056	-0.040	1.000
IV24	-0.108	-0.091	-0.067	0.139	-0.015	-0.002	-0.047	-0.024	-0.027	0.239	-0.013	-0.013	-0.042	-0.025	-0.009	-0.012	-0.015	-0.062	-0.005	-0.008	-0.008	-0.005	-0.056
IV25	0.052	0.109	-0.028	0.018	-0.011	-0.063	-0.033	-0.017	-0.019	-0.011	-0.009	0.404	-0.030	-0.018	-0.007	-0.009	-0.011	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV26	-0.062	-0.155	-0.041	-0.011	0.136	-0.058	0.032	-0.011	-0.051	-0.014	-0.081	0.161	0.125	0.120	0.113	0.046	0.016	-0.217	-0.047	0.171	0.112	0.204	-0.094
IV27	0.017	0.144	0.050	0.102	0.030	-0.020	0.068	-0.056	-0.112	-0.027	0.189	-0.007	0.877	-0.031	-0.051	-0.066	-0.084	-0.319	-0.029	-0.041	-0.041	-0.029	-0.306
IV28	0.006	-0.056	-0.055	0.003	0.057	0.096	-0.087	-0.065	0.047	-0.042	-0.036	-0.036	-0.072	0.680	-0.025	-0.033	-0.042	-0.169	-0.014	0.174	-0.021	-0.014	-0.152
IV29	-0.056	-0.016	-0.038	0.144	-0.027	-0.105	-0.021	0.056	0.133	0.121	-0.023	-0.023	-0.074	0.331	0.463	-0.021	-0.027	-0.109	-0.009	-0.013	-0.013	-0.009	-0.098
IV30	-0.085	-0.017	-0.094	0.026	-0.015	-0.002	-0.047	0.145	-0.027	-0.015	-0.013	-0.013	-0.042	-0.025	-0.009	0.629	-0.015	-0.062	-0.005	-0.008	-0.008	-0.005	-0.056
IV31	0.022	0.015	-0.053	0.080	-0.031	-0.004	0.010	-0.049	0.024	0.098	-0.027	-0.027	-0.086	-0.052	-0.019	-0.024	0.742	-0.033	-0.011	-0.015	-0.015	-0.011	-0.113
IV32	0.030	0.027	0.006	-0.031	-0.024	-0.031	-0.008	0.069	0.056	-0.024	-0.021	-0.021	0.214	0.062	-0.015	-0.019	-0.024	-0.099	-0.009	-0.012	-0.012	-0.009	-0.089
IV33	0.020	-0.029	0.049	-0.062	-0.011	0.060	-0.033	-0.017	-0.019	-0.011	-0.009	-0.009	-0.030	-0.018	-0.007	0.444	-0.011	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV34	-0.063	0.030	-0.057	0.010	0.022	-0.112	0.020	0.126	0.050	0.022	0.006	-0.049	-0.331	-0.199	-0.073	-0.034	-0.072	0.916	-0.042	-0.059	-0.059	-0.042	-0.438
IV35	-0.085	-0.042	0.015	-0.031	-0.015	-0.089	0.161	-0.024	-0.027	-0.015	-0.013	-0.013	-0.042	-0.025	-0.009	-0.012	-0.015	0.030	0.706	-0.008	-0.008	-0.005	-0.056
IV36	0.028	-0.066	0.042	-0.031	-0.015	0.085	-0.047	-0.024	-0.027	-0.015	-0.013	-0.013	-0.042	0.136	-0.009	-0.012	-0.015	-0.062	-0.005	0.496	-0.008	-0.005	-0.056
IV37	0.020	0.075	0.049	0.018	-0.011	0.060	-0.033	-0.017	-0.019	-0.011	-0.009	-0.009	-0.030	-0.018	-0.007	-0.009	0.349	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV38	0.020	-0.029	0.049	0.018	-0.011	0.060	-0.033	-0.017	-0.019	-0.011	-0.009	-0.009	0.126	-0.018	-0.007	-0.009	-0.011	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV39	0.005	-0.066	0.042	-0.031	-0.015	-0.002	0.057	-0.024	-0.027	-0.015	-0.013	-0.013	-0.042	-0.025	-0.009	-0.012	-0.015	-0.062	-0.005	-0.008	0.496	0.706	-0.056
IV40	0.077	-0.105	0.062	-0.163	-0.028	0.129	-0.027	-0.067	-0.012	-0.075	-0.105	0.003	-0.337	-0.202	-0.002	-0.036	-0.122	-0.426	-0.042	-0.060	0.033	-0.042	0.932
IV41	-0.140	-0.064	-0.028	0.178	-0.011	-0.063	-0.033	-0.017	-0.019	0.349	-0.009	-0.009	-0.030	-0.018	-0.007	-0.009	-0.011	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV42	0.052	0.109	-0.028	0.018	-0.011	-0.063	-0.033	-0.017	-0.019	-0.011	-0.009	0.404	-0.030	-0.018	-0.007	-0.009	-0.011	-0.044	-0.004	-0.005	-0.005	-0.004	-0.040
IV43	-0.080	-0.160	-0.059	0.037	0.153	-0.009	-0.013	0.028	-0.033	-0.033	-0.089	0.033	0.099	0.155	0.216	0.058	-0.006	-0.171	0.026	0.193	0.141	0.247	-0.179
IV44	-0.076	-0.018	-0.112	0.052	0.048	-0.110	0.072	-0.015	0.048	-0.004	0.026	0.026	0.073	0.100	-0.023	0.013	0.048	0.198	0.035	0.049	-0.053	0.035	-0.372
IV45	-0.161	-0.145	-0.062	-0.002	-0.087	0.008	0.058	0.046	0.016	-0.087	-0.100	0.001	-0.178	-0.012	0.108	0.139	0.089	0.101	0.062	0.001	0.088	0.062	-0.078
IV46	0.154	0.003	0.038	-0.025	0.074	-0.009	0.009	-0.067	-0.039	-0.015	0.089	0.038	0.122	-0.178	-0.045	-0.039	-0.103	0.020	-0.067	-0.007	0.080	-0.067	0.013
IV47	-0.139	0.054	-0.020	0.002	-0.073	-0.056	0.093	0.060	0.047	-0.026	-0.050	-0.104	-0.149	0.098	-0.073	0.024	0.068	0.106	0.090	0.034	-0.060	-0.042	-0.034
IV48	-0.099	-0.012	-0.009	0.040	-0.038	0.104	-0.074	-0.060	-0.067	0.068	-0.033	0.089	-0.014	0.071	0.148	-0.030	0.068	-0.041	-0.013	-0.019	-0.019	-0.013	-0.021
IV49	-0.021	-0.051	-0.071	0.124	-0.019	-0.038	0.028	-0.030	0.094	-0.019	-0.016	-0.016	-0.052	0.101	-0.011	-0.015	-0.019	-0.001	-0.007	-0.009	-0.009	0.575	-0.069
IV50	0.033	-0.080	-0.005	0.028	0.033	0.051	-0.120	0.087	-0.037	0.033	-0.043	0.053	0.078	0.075	0.105	0.066	0						



	IV24	IV25	IV26	IV27	IV28	IV29	IV30	IV31	IV32	IV33	IV34	IV35	IV36	IV37	IV38	IV39	IV40	IV41	IV42	IV43	IV44	IV45	IV46
IV1	-0.108	0.052	-0.062	0.017	0.006	-0.056	-0.085	0.022	0.030	0.020	-0.063	-0.085	0.028	0.020	0.020	0.005	0.077	-0.140	0.052	-0.080	-0.076	-0.161	0.154
IV2	-0.091	0.109	-0.155	0.144	-0.056	-0.016	-0.017	0.015	0.027	-0.029	0.030	-0.042	-0.066	0.075	-0.029	-0.066	-0.105	-0.064	0.109	-0.160	-0.018	-0.145	0.003
IV3	-0.067	-0.028	-0.041	0.050	-0.055	-0.038	-0.094	-0.053	0.006	0.049	-0.057	0.015	0.042	0.049	0.049	0.042	0.062	-0.028	-0.028	-0.059	-0.112	-0.062	0.038
IV4	0.139	0.018	-0.011	0.102	0.003	0.144	0.026	0.080	-0.031	-0.062	0.010	-0.031	-0.031	0.018	0.018	-0.031	-0.163	0.178	0.018	0.037	0.052	-0.002	-0.025
IV5	-0.015	-0.011	0.136	0.030	0.057	-0.027	-0.015	-0.031	-0.024	-0.011	0.022	-0.015	-0.015	-0.011	-0.011	-0.015	-0.028	-0.011	-0.011	0.153	0.048	-0.087	0.074
IV6	-0.002	-0.063	-0.058	-0.020	0.096	-0.105	-0.002	-0.004	-0.031	0.060	-0.112	-0.089	0.085	0.060	0.060	-0.002	0.129	-0.063	-0.063	-0.009	-0.110	0.008	-0.009
IV7	-0.047	-0.033	0.032	0.068	-0.087	-0.021	-0.047	0.010	-0.008	-0.033	0.020	0.161	-0.047	-0.033	-0.033	0.057	-0.027	-0.033	-0.033	-0.013	0.072	0.058	0.009
IV8	-0.024	-0.017	-0.011	-0.056	-0.065	0.056	0.145	-0.049	0.069	-0.017	0.126	-0.024	-0.024	-0.017	-0.017	-0.024	-0.067	-0.017	-0.017	0.028	-0.015	0.046	-0.067
IV9	-0.027	-0.019	-0.051	-0.112	0.047	0.133	-0.027	0.024	0.056	-0.019	0.050	-0.027	-0.027	-0.019	-0.019	-0.027	-0.012	-0.019	-0.019	-0.033	0.048	0.016	-0.039
IV10	0.239	-0.011	-0.014	-0.027	-0.042	0.121	-0.015	0.098	-0.024	-0.011	0.022	-0.015	-0.015	-0.011	-0.011	-0.015	-0.075	0.349	-0.011	-0.033	-0.004	-0.087	-0.015
IV11	-0.013	-0.009	-0.081	0.189	-0.036	-0.023	-0.013	-0.027	-0.021	-0.009	0.006	-0.013	-0.013	-0.009	-0.009	-0.013	-0.105	-0.009	-0.009	-0.089	0.026	-0.100	0.089
IV12	-0.013	0.404	0.161	-0.007	-0.036	-0.023	-0.013	-0.027	-0.021	-0.009	-0.049	-0.013	-0.013	-0.009	-0.009	-0.013	0.003	-0.009	0.404	0.033	0.026	0.001	0.038
IV13	-0.042	-0.030	0.125	0.877	-0.072	-0.074	-0.042	-0.086	0.214	-0.030	-0.331	-0.042	-0.042	-0.030	0.126	-0.042	-0.337	-0.030	-0.030	0.099	0.073	-0.178	0.122
IV14	-0.025	-0.018	0.120	-0.031	0.680	0.331	-0.025	-0.052	0.062	-0.018	-0.199	-0.025	0.136	-0.018	-0.018	-0.025	-0.202	-0.018	-0.018	0.155	0.100	-0.012	-0.178
IV15	-0.009	-0.007	0.113	-0.051	-0.025	0.463	-0.009	-0.019	-0.015	-0.007	-0.073	-0.009	-0.009	-0.007	-0.007	-0.009	0.002	-0.007	-0.007	0.216	-0.023	0.108	-0.045
IV16	-0.012	-0.009	0.046	-0.066	-0.033	-0.021	0.629	-0.024	-0.019	0.444	-0.034	-0.012	-0.012	-0.009	-0.009	-0.012	-0.036	-0.009	-0.009	0.568	0.013	0.139	-0.039
IV17	-0.015	-0.011	0.016	-0.084	-0.042	-0.027	-0.015	0.742	-0.024	-0.011	-0.072	-0.015	-0.015	0.349	-0.011	-0.015	-0.122	-0.011	-0.011	-0.006	0.048	0.089	-0.103
IV18	-0.062	-0.044	-0.217	-0.319	-0.169	-0.109	-0.062	-0.033	-0.099	-0.044	0.916	0.030	-0.062	-0.044	-0.044	-0.062	-0.426	-0.044	-0.044	-0.171	0.198	0.101	0.020
IV19	-0.005	-0.004	-0.047	-0.021	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	0.706	-0.005	-0.004	-0.004	-0.005	-0.042	-0.004	-0.004	0.026	0.035	0.062	-0.067
IV20	-0.008	-0.005	0.171	-0.041	0.174	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	-0.008	0.496	-0.005	-0.005	-0.008	-0.060	-0.005	-0.005	0.193	0.049	0.001	-0.007
IV21	-0.008	-0.005	0.112	-0.041	-0.021	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	-0.008	-0.008	-0.005	-0.005	0.496	0.033	-0.005	-0.005	0.141	-0.053	0.088	0.080
IV22	-0.005	-0.004	0.204	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	-0.004	-0.004	0.706	-0.042	-0.004	-0.004	0.247	0.035	0.062	-0.067
IV23	-0.056	-0.040	-0.094	-0.306	-0.152	-0.098	-0.056	-0.113	-0.089	-0.040	-0.438	-0.056	-0.056	-0.040	-0.040	-0.056	0.932	-0.040	-0.040	-0.179	-0.372	-0.078	0.013
IV24	1.000	-0.005	0.112	-0.041	-0.021	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	-0.008	-0.008	-0.005	-0.005	-0.008	0.033	0.706	-0.005	0.088	0.049	0.001	0.080
IV25	-0.005	1.000	0.037	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	-0.004	-0.004	-0.005	-0.042	-0.004	1.000	0.226	0.035	-0.061	0.057
IV26	0.112	0.037	1.000	0.049	0.119	0.092	0.171	0.046	0.197	-0.047	-0.239	-0.007	0.053	0.037	0.121	0.112	-0.053	0.121	0.037	0.831	0.055	0.088	-0.248
IV27	-0.041	-0.029	0.049	1.000	-0.112	-0.072	-0.041	-0.084	-0.066	-0.029	-0.323	-0.041	-0.041	-0.029	-0.029	-0.041	-0.328	-0.029	-0.029	0.223	0.109	-0.181	0.126
IV28	-0.021	-0.014	0.119	-0.112	1.000	-0.036	-0.021	-0.042	-0.033	-0.014	-0.160	-0.021	-0.021	-0.014	-0.014	-0.021	-0.163	-0.014	-0.014	0.199	0.015	0.002	-0.053
IV29	-0.013	-0.009	0.092	-0.072	-0.036	1.000	-0.013	-0.027	-0.021	-0.009	-0.103	-0.013	-0.013	-0.009	-0.009	-0.013	-0.105	-0.009	-0.009	0.124	0.086	0.052	-0.114
IV30	-0.008	-0.005	0.171	-0.041	-0.021	-0.013	1.000	-0.015	-0.012	-0.005	-0.059	-0.008	-0.008	-0.005	-0.005	-0.008	-0.060	-0.005	-0.005	0.193	-0.053	0.088	-0.095
IV31	-0.015	-0.011	0.046	-0.084	-0.042	-0.027	-0.015	1.000	-0.024	-0.011	-0.120	-0.015	-0.015	-0.011	-0.011	-0.015	-0.122	-0.011	-0.011	0.047	0.099	0.089	-0.103
IV32	-0.012	-0.009	0.197	-0.066	-0.033	-0.021	-0.012	-0.024	1.000	-0.009	-0.094	-0.012	-0.012	-0.009	-0.009	-0.012	-0.096	-0.009	-0.009	0.191	0.078	0.029	-0.039
IV33	-0.005	-0.004	-0.047	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	1.000	-0.042	-0.005	-0.005	-0.004	-0.004	-0.005	-0.042	-0.004	-0.004	0.048	0.035	0.062	0.057
IV34	-0.059	-0.042	-0.239	-0.323	-0.160	-0.103	-0.059	-0.120	-0.094	-0.042	1.000	-0.059	-0.059	-0.042	-0.042	-0.059	-0.470	-0.042	-0.042	-0.204	0.212	0.118	0.009
IV35	-0.008	-0.005	-0.007	-0.041	-0.021	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	1.000	-0.008	-0.005	-0.005	-0.008	-0.060	-0.005	-0.005	0.036	0.049	0.088	-0.095
IV36	-0.008	-0.005	0.053	-0.041	-0.021	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	-0.008	1.000	-0.005	-0.005	-0.008	-0.060	-0.005	-0.005	0.036	0.049	-0.086	-0.095
IV37	-0.005	-0.004	0.037	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	1.000	-0.004	-0.004	-0.005	-0.042	-0.004	0.026	-0.109	-0.061	-0.067
IV38	-0.005	-0.004	0.121	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	-0.004	1.000	-0.005	-0.042	-0.004	-0.004	0.099	-0.109	-0.061	-0.067
IV39	-0.008	-0.005	0.112	-0.041	-0.021	-0.013	-0.008	-0.015	-0.012	-0.005	-0.059	-0.008	-0.008	-0.005	-0.005	1.000	-0.060	-0.005	-0.005	0.141	-0.053	0.088	-0.007
IV40	0.033	-0.042	-0.053	-0.328	-0.163	-0.103	-0.060	-0.122	-0.096	-0.042	-0.470	-0.060	-0.060	-0.042	-0.042	-0.060	1.000	-0.042	-0.042	-0.118	-0.382	-0.043	0.039
IV41	0.706	-0.004	0.121	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	-0.004	-0.004	-0.005	-0.042	1.000	-0.004	0.099	0.035	-0.061	0.057
IV42	-0.005	1.000	0.037	-0.029	-0.014	-0.009	-0.005	-0.011	-0.009	-0.004	-0.042	-0.005	-0.005	-0.004	-0.004	-0.005	-0.042	-0.004	1.000	0.226	0.035	-0.061	0.057
IV43	0.088	0.026	0.831	0.023	0.199	0.124	0.193	0.047	0.191	-0.048	-0.204	0.036	0.036	0.026	0.094	0.141	-0.118	0.099	0.026	1.000	0.041	0.123	-0.228
IV44	0.049	0.035	0.055	0.109	0.015	0.086	-0.053	0.099	0.078	0.035	0.212	0.049	0.049	-0.109	-0.109	-0.053	-0.382	0.035	0.035	0.041	1.000	0.471	0.011
IV45	0.001	-0.061	0.088	-0.181	0.002	0.052	0.088	0.089	0.029	0.062	0.118	0.088	-0.086	-0.061	-0.061	0.088	-0.043	-0.061	-0.061	0.123	0.471	1.000	-0.052
IV46	0.080	0.057	-0.248	0.126	-0.053	-0.114	-0.095	-0.103	-0.039	0.057	0.009	-0.095	-0.095	-0.067	-0.067	0.039	0.057	0.057	0.057	0.228	0.011	-0.052	1.000
IV47	-0.060	-0.042	0.052	-0.159	0.019	0.059	0.034	0.021	0.083	-0.042	0.124	0.127	0.034	0.090	-0.042	-0.060	-0.060	-0.042	-0.042	0.043	0.009	0.013	-0.745
IV48	-0.019	-0.013	0.131	-0.010	0.111	-0.033	-0.019	0.068	-0.030	-0.013	-0.031	-0.019	-0.019	-0.013	-0.013	-0.019	0.005	-0.013	-0.013	0.134	-0.047	0.002	-0.236
IV49	-0.009	-0.007	0.113	-0.051	-0.025	0.224	-0.009	0.190	-0.005	-0.007	-0.073	-0.009	-0.009	-0.007	-0.007	0.403	-0.074	-0.007	-0.007	0.173	0.060	0.108	-0.116
IV50	-0.025	-0.018	0.250	0.085	-0.003	0.053	0.140	0.033	-0.039	-0.018	-0.163	-0.025	0.140	-0.018	0.215	-0.025	0.016	-0.018	-0.018	0.187	-0.006		



	IV47	IV48	IV49	IV50	IV51	IV52	IV53	IV54	IV55	IV56	IV57	IV58	IV59	IV60	IV61	IV62	IV63	IV64	IV65	IV66	IV67	IV68	IV69	IV70	IV71	IV72	
IV1	-0.139	-0.099	-0.021	0.033	0.013	0.013	-0.078	-0.019	-0.108	-0.016	-0.005	-0.007	0.056	-0.012	-0.003	-0.025	0.021	0.018	-0.068	0.031	-0.028	0.053	0.040	0.014	-0.039	0.014	
IV2	0.054	-0.012	-0.051	-0.080	-0.010	0.066	0.117	0.017	-0.099	0.077	0.094	0.076	0.011	0.015	0.029	-0.091	-0.103	-0.108	-0.047	0.007	0.069	-0.077	-0.064	0.071	0.129	-0.039	
IV3	-0.020	-0.009	-0.071	-0.005	-0.013	0.046	0.038	0.090	0.149	0.016	-0.004	0.037	-0.012	0.071	-0.071	-0.037	0.002	0.025	0.053	0.011	0.021	-0.086	-0.090	-0.097	-0.005	0.026	
IV4	0.002	0.040	0.124	-0.028	-0.088	0.104	0.037	0.051	-0.090	0.061	0.118	-0.018	0.030	-0.006	-0.015	0.003	0.128	0.070	0.025	0.013	0.060	-0.021	-0.052	0.051	-0.025	0.093	
IV5	-0.073	-0.038	-0.019	0.033	-0.010	0.024	-0.108	-0.108	0.054	-0.033	-0.067	-0.038	0.142	-0.031	-0.019	-0.040	0.075	0.105	0.137	-0.069	0.015	0.041	0.044	-0.064	-0.120	0.062	
IV6	-0.056	0.104	-0.038	0.051	-0.042	-0.080	-0.001	0.103	-0.009	-0.010	-0.043	-0.095	0.027	-0.004	-0.038	0.083	0.112	0.133	0.102	0.090	-0.026	-0.057	-0.057	0.006	-0.066	-0.057	
IV7	0.093	-0.074	0.028	-0.120	0.076	0.008	0.031	-0.044	0.011	0.007	0.089	-0.041	-0.028	0.116	0.113	-0.006	-0.106	-0.069	-0.106	-0.124	0.023	0.070	0.081	-0.063	0.046	0.001	
IV8	0.060	-0.060	-0.030	0.087	0.010	0.038	-0.043	-0.084	0.012	-0.080	0.066	0.161	-0.101	-0.049	-0.030	-0.067	-0.081	-0.066	-0.030	0.054	0.068	-0.017	-0.058	0.016	0.028	-0.038	
IV9	0.047	-0.067	0.094	-0.037	0.006	0.043	0.020	0.094	-0.011	-0.040	0.000	0.108	0.055	-0.054	-0.033	-0.113	-0.013	-0.074	-0.046	0.028	-0.032	0.033	0.104	0.007	0.098	0.102	
IV10	-0.026	0.068	-0.019	0.033	-0.063	0.024	0.014	-0.047	-0.072	0.064	-0.014	-0.084	0.005	-0.031	-0.019	0.092	0.012	-0.042	-0.061	0.023	-0.094	-0.038	-0.107	-0.064	-0.060	0.062	
IV11	-0.050	-0.033	-0.016	-0.043	0.021	0.021	0.065	-0.005	-0.062	0.097	0.080	0.047	-0.055	-0.027	-0.016	0.003	-0.044	-0.036	0.061	-0.024	0.075	-0.066	-0.080	0.043	0.033	-0.075	
IV12	-0.104	0.089	-0.016	0.053	-0.039	0.021	-0.005	-0.075	0.083	0.097	0.019	0.047	-0.055	-0.027	-0.016	0.003	0.028	-0.036	-0.053	-0.024	-0.019	0.024	0.021	0.218	0.033	-0.006	
IV13	-0.149	-0.014	-0.052	0.078	-0.423	-0.003	0.023	0.023	0.023	-0.117	0.142	0.165	-0.120	-0.177	0.026	0.038	0.212	-0.005	-0.053	0.024	-0.151	0.082	0.093	-0.174	0.098	-0.022	0.031
IV14	0.098	0.071	0.101	0.075	-0.476	-0.062	-0.029	0.086	0.080	-0.090	-0.014	-0.100	-0.063	-0.052	-0.031	0.160	0.035	0.023	-0.070	-0.076	-0.104	-0.053	-0.111	-0.073	0.045	0.044	
IV15	-0.073	0.148	-0.011	0.105	-0.113	0.015	0.046	0.046	0.058	-0.089	-0.030	0.070	0.072	-0.019	-0.011	-0.104	0.173	0.213	-0.037	0.255	-0.057	-0.047	-0.012	0.123	-0.216	0.044	
IV16	0.024	-0.030	-0.015	0.066	-0.058	0.019	0.059	0.059	-0.057	0.027	0.046	0.071	-0.050	-0.024	-0.015	-0.025	-0.040	-0.033	-0.048	-0.016	0.063	-0.061	-0.127	-0.080	0.108	0.044	
IV17	0.068	0.068	-0.019	0.033	0.095	0.024	0.014	0.014	0.054	0.064	-0.067	0.100	0.005	-0.031	-0.019	-0.084	-0.051	-0.042	0.137	0.023	0.015	-0.077	-0.086	0.012	0.058	0.092	
IV18	0.106	-0.041	-0.001	-0.174	0.367	0.040	-0.003	-0.091	-0.088	0.018	0.031	0.070	0.136	0.060	-0.001	-0.175	-0.140	-0.145	0.002	0.007	0.050	0.029	0.023	-0.070	0.211	-0.160	
IV19	0.090	-0.013	-0.007	-0.018	0.033	0.009	0.026	0.026	0.150	-0.096	0.032	0.083	-0.022	-0.011	-0.007	-0.060	-0.018	-0.015	-0.021	-0.024	0.043	-0.027	-0.025	-0.035	0.041	-0.030	
IV20	0.034	-0.019	-0.009	-0.025	-0.161	0.012	-0.083	0.037	-0.036	-0.040	-0.059	-0.064	0.104	-0.015	-0.009	0.002	0.100	0.125	-0.030	-0.034	-0.100	0.196	0.124	0.025	-0.176	0.194	
IV21	-0.060	-0.019	-0.009	-0.025	-0.057	0.012	0.037	0.037	-0.036	0.056	0.046	0.027	-0.032	-0.015	-0.009	0.002	0.100	0.271	0.068	-0.034	0.061	-0.038	-0.012	0.100	-0.176	0.134	
IV22	-0.042	-0.013	0.575	-0.018	-0.114	0.009	-0.144	0.026	-0.025	-0.096	0.032	-0.045	-0.022	-0.011	-0.007	0.063	-0.018	0.191	-0.021	-0.024	-0.108	0.083	0.179	-0.035	-0.042	-0.030	
IV23	-0.034	-0.021	-0.069	0.036	0.348	0.040	0.001	0.001	0.138	-0.081	-0.120	0.025	0.049	-0.017	0.009	-0.052	0.049	0.040	-0.038	0.103	-0.038	0.088	0.215	-0.058	-0.092	-0.050	
IV24	-0.060	-0.019	-0.009	-0.025	-0.057	0.012	-0.083	-0.083	-0.036	-0.040	-0.059	-0.064	-0.032	-0.015	-0.009	0.089	0.225	0.125	0.165	0.147	-0.046	0.040	0.017	0.100	-0.294	0.194	
IV25	-0.042	-0.013	-0.007	-0.018	-0.114	0.009	0.026	-0.144	-0.025	0.039	0.032	0.083	-0.022	-0.011	-0.007	-0.060	-0.018	-0.015	-0.021	-0.024	-0.043	0.083	0.012	0.177	0.041	0.137	
IV26	0.052	0.131	0.113	0.250	-0.277	-0.008	-0.017	0.026	0.056	-0.047	0.028	0.007	0.012	-0.043	0.258	-0.055	0.161	0.196	-0.021	0.016	-0.025	0.090	0.056	0.128	-0.190	0.119	
IV27	-0.159	-0.010	-0.051	0.085	-0.347	-0.006	-0.012	-0.012	-0.111	0.154	0.133	-0.088	-0.173	0.030	-0.051	0.195	0.001	-0.016	-0.012	-0.146	0.141	-0.138	-0.221	0.094	0.004	0.041	
IV28	0.019	0.111	-0.025	-0.003	-0.396	-0.091	-0.086	0.101	0.000	-0.035	0.002	-0.139	0.019	-0.042	-0.025	0.140	0.076	0.056	-0.044	-0.046	-0.126	0.048	0.000	-0.049	0.021	0.112	
IV29	0.059	-0.033	0.224	0.053	-0.281	0.021	0.065	0.065	0.010	-0.126	0.019	0.047	-0.055	-0.027	-0.016	0.003	0.028	-0.036	-0.053	-0.024	-0.019	-0.066	-0.051	-0.044	-0.103	0.062	
IV30	0.034	-0.019	-0.009	0.140	-0.057	0.012	0.037	0.037	-0.036	0.056	-0.059	0.027	-0.032	-0.015	-0.009	0.002	-0.025	-0.021	-0.030	0.026	0.061	-0.038	-0.091	-0.050	0.058	0.134	
IV31	0.021	0.068	0.190	0.033	0.042	0.024	0.014	0.014	0.054	0.015	-0.067	0.054	0.005	-0.031	-0.019	-0.040	-0.051	-0.042	0.087	-0.008	-0.094	0.041	0.020	0.012	0.029	-0.027	
IV32	0.083	-0.030	-0.015	-0.039	-0.256	0.019	0.059	0.059	0.102	-0.034	0.073	0.013	-0.050	-0.024	0.247	-0.025	-0.040	-0.033	-0.048	-0.054	-0.108	0.039	0.028	0.016	-0.057	-0.069	
IV33	-0.042	-0.013	-0.007	-0.018	-0.114	0.009	0.026	0.026	-0.025	-0.039	0.032	-0.045	-0.022	-0.011	-0.007	0.063	-0.018	-0.015	-0.021	-0.024	-0.033	-0.027	-0.054	-0.035	-0.042	-0.030	
IV34	0.124	-0.031	-0.073	-0.163	0.367	0.034	-0.024	-0.113	-0.092	0.077	0.104	0.107	0.081	0.070	0.004	-0.179	-0.128	-0.136	0.001	0.026	0.106	-0.051	-0.058	-0.057	0.236	-0.161	
IV35	0.127	-0.019	-0.009	-0.025	0.047	0.012	0.037	0.037	0.089	-0.136	-0.059	0.027	0.104	-0.015	-0.009	-0.085	-0.025	-0.021	-0.030	-0.034	0.007	0.040	0.033	-0.050	0.000	-0.043	
IV36	0.034	-0.019	-0.009	0.140	-0.161	0.012	0.037	0.037	-0.036	-0.040	-0.059	-0.064	-0.032	-0.015	-0.009	0.089	-0.025	-0.021	-0.030	-0.034	-0.154	0.040	0.047	0.025	-0.059	0.075	
IV37	0.090	-0.013	-0.007	-0.018	0.033	0.009	0.026	0.026	-0.025	0.039	-0.116	-0.045	0.169	-0.011	-0.007	-0.060	-0.018	-0.015	0.117	0.061	0.043	-0.027	0.012	-0.035	0.041	0.137	
IV38	-0.042	-0.013	-0.007	0.215	-0.114	0.009	0.026	0.026	-0.025	-0.096	0.032	-0.045	-0.022	-0.011	-0.007	0.063	0.158	-0.015	0.255	-0.024	0.043	0.083	-0.033	-0.033	-0.042	0.137	
IV39	-0.060	-0.019	0.403	-0.025	-0.161	0.012	-0.083	0.037	-0.036	-0.040	0.046	-0.064	-0.032	-0.015	-0.009	0.089	-0.025	0.271	-0.030	-0.034	-0.046	0.040	0.106	0.025	-0.059	0.075	
IV40	-0.060	0.005	-0.074	0.016	0.373	-0.023	0.006	0.028	0.154	-0.126	-0.199	0.027	0.075	-0.028	0.002	-0.065	0.099	0.131	0.013	0.165	-0.051	0.100	0.227	-0.011	-0.177	-0.026	
IV41	-0.042	-0.013	-0.007	-0.018	-0.114	0.009	0.026	-0.144	-0.025	0.039	0.032	-0.045	-0.022	-0.011	-0.007	0.063	0.158	-0.015	-0.021	-0.024	-0.108	0.083	0.012	-0.035	-0.207	0.137	
IV42	-0.042	-0.013	-0.007	-0.018	-0.114	0.009	0.026	-0.144	-0.025	0.039	0.032	0.083	-0.022	-0.011	-0.007	-0.060	-0.018	-0.015	-0.021	-0.024	-0.033	0.083	0.012	0.177	0.041	0.137	
IV43	0.043	0.134	0.216	0.187	-0.311	-0.024	-0.090	0.060	0.028	-0.106	-0.012	-0.005	-0.004	-0.059	0.173	-0.009	0.290	0.281	-0.008	0.018	-0.101	0.149	0.098	0.123	-0.241	0.114	
IV44	0.009	-0.047	0.060	-0.006	-0.135	0.116	0.052	0.003	-0.047	0.242	0.235	0.122	-0.124	0.048	-0.023	-0.048	-0.139	-0.131	0.037	-0.109	0.067	-0.163	-0.179	-0.115	0.086	-0.068	
IV45	0.013	0.002	0.108	0.059	0.032	0.082	-0.014																				

## APPENDIX 9 – COMMUNALITIES

	Initial	Extraction
IV1	1.000	0.571
IV2	1.000	0.697
IV3	1.000	0.749
IV4	1.000	0.796
IV5	1.000	0.684
IV6	1.000	0.901
IV7	1.000	0.862
IV8	1.000	0.684
IV9	1.000	0.812
IV10	1.000	0.587
IV11	1.000	0.636
IV12	1.000	0.543
IV13	1.000	0.932
IV14	1.000	0.868
IV15	1.000	0.754
IV16	1.000	0.877
IV17	1.000	0.902
IV18	1.000	0.938
IV19	1.000	0.813
IV20	1.000	0.780
IV21	1.000	0.701
IV22	1.000	0.834
IV23	1.000	0.951
IV24	1.000	0.790
IV25	1.000	0.932
IV26	1.000	0.807
IV27	1.000	0.887
IV28	1.000	0.833
IV29	1.000	0.790
IV30	1.000	0.742
IV31	1.000	0.836
IV32	1.000	0.680
IV33	1.000	0.701
IV34	1.000	0.945
IV35	1.000	0.839
IV36	1.000	0.759
IV37	1.000	0.608
IV38	1.000	0.680
IV39	1.000	0.866
IV40	1.000	0.957
IV41	1.000	0.835
IV42	1.000	0.932
IV43	1.000	0.790
IV44	1.000	0.761
IV45	1.000	0.772
IV46	1.000	0.883
IV47	1.000	0.870
IV48	1.000	0.701
IV49	1.000	0.707
IV50	1.000	0.751
IV51	1.000	0.812
IV52	1.000	0.536
IV53	1.000	0.762
IV54	1.000	0.630
IV55	1.000	0.694
IV56	1.000	0.738
IV57	1.000	0.701
IV58	1.000	0.921
IV59	1.000	0.729
IV60	1.000	0.707
IV61	1.000	0.640
IV62	1.000	0.910
IV63	1.000	0.824
IV64	1.000	0.848
IV65	1.000	0.766
IV66	1.000	0.697
IV67	1.000	0.789
IV68	1.000	0.821
IV69	1.000	0.751
IV70	1.000	0.680
IV71	1.000	0.588
IV72	1.000	0.627



## APPENDIX 10 – TOTAL VARIANCE EXPLAINED

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.422	6.141	6.141	4.422	6.141	6.141	3.017	4.190	4.190
2	3.976	5.522	11.664	3.976	5.522	11.664	2.986	4.148	8.338
3	3.188	4.427	16.091	3.188	4.427	16.091	2.508	3.484	11.821
4	2.992	4.155	20.246	2.992	4.155	20.246	2.485	3.451	15.272
5	2.707	3.760	24.006	2.707	3.760	24.006	2.457	3.413	18.685
6	2.516	3.495	27.501	2.516	3.495	27.501	2.409	3.346	22.031
7	2.367	3.288	30.789	2.367	3.288	30.789	2.353	3.268	25.298
8	2.218	3.080	33.869	2.218	3.080	33.869	2.205	3.063	28.361
9	2.122	2.947	36.816	2.122	2.947	36.816	2.003	2.782	31.143
10	2.097	2.912	39.729	2.097	2.912	39.729	1.951	2.710	33.853
11	2.004	2.784	42.513	2.004	2.784	42.513	1.950	2.708	36.560
12	1.942	2.697	45.210	1.942	2.697	45.210	1.921	2.668	39.228
13	1.813	2.519	47.728	1.813	2.519	47.728	1.887	2.620	41.849
14	1.741	2.418	50.146	1.741	2.418	50.146	1.846	2.564	44.413
15	1.654	2.297	52.443	1.654	2.297	52.443	1.830	2.542	46.955
16	1.574	2.187	54.629	1.574	2.187	54.629	1.757	2.440	49.395
17	1.549	2.151	56.780	1.549	2.151	56.780	1.748	2.428	51.824
18	1.491	2.071	58.851	1.491	2.071	58.851	1.733	2.407	54.231
19	1.460	2.027	60.878	1.460	2.027	60.878	1.659	2.304	56.534
20	1.419	1.971	62.849	1.419	1.971	62.849	1.645	2.285	58.820
21	1.359	1.887	64.736	1.359	1.887	64.736	1.632	2.267	61.086
22	1.257	1.745	66.481	1.257	1.745	66.481	1.567	2.176	63.263
23	1.244	1.728	68.210	1.244	1.728	68.210	1.535	2.132	65.395
24	1.207	1.676	69.885	1.207	1.676	69.885	1.522	2.113	67.508
25	1.143	1.588	71.473	1.143	1.588	71.473	1.505	2.090	69.598
26	1.119	1.554	73.027	1.119	1.554	73.027	1.457	2.024	71.622
27	1.069	1.484	74.511	1.069	1.484	74.511	1.394	1.935	73.558
28	1.032	1.434	75.945	1.032	1.434	75.945	1.371	1.905	75.463
29	1.015	1.410	77.355	1.015	1.410	77.355	1.362	1.892	77.355
30	0.995	1.382	78.736						
31	0.937	1.302	80.038						
32	0.914	1.269	81.307						
33	0.874	1.213	82.521						
34	0.822	1.141	83.662						
35	0.811	1.127	84.789						
36	0.742	1.031	85.820						
37	0.730	1.014	86.834						
38	0.701	0.973	87.807						
39	0.689	0.957	88.764						
40	0.627	0.871	89.634						
41	0.613	0.851	90.485						
42	0.607	0.844	91.329						
43	0.537	0.746	92.075						
44	0.520	0.722	92.797						
45	0.493	0.685	93.482						
46	0.480	0.666	94.148						
47	0.422	0.586	94.734						
48	0.398	0.553	95.287						
49	0.351	0.488	95.775						
50	0.325	0.451	96.226						
51	0.310	0.431	96.658						
52	0.290	0.403	97.060						
53	0.283	0.393	97.453						
54	0.238	0.330	97.783						
55	0.218	0.303	98.086						
56	0.212	0.294	98.380						
57	0.182	0.252	98.632						
58	0.177	0.246	98.878						
59	0.170	0.236	99.115						
60	0.141	0.196	99.310						
61	0.126	0.175	99.486						
62	0.116	0.162	99.647						
63	0.090	0.125	99.773						
64	0.076	0.105	99.878						
65	0.057	0.079	99.956						
66	0.013	0.018	99.975						
67	0.011	0.016	99.990						
68	0.007	0.010	100.000						
69	5.236E-16	7.272E-16	100.000						
70	2.893E-16	4.018E-16	100.000						
71	1.724E-16	2.394E-16	100.000						
72	-1.115E-16	-1.548E-16	100.000						

## APPENDIX 11 – COMPONENT MATRIX

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
IV34	-0.632	0.009	0.388	-0.378	0.180	-0.231	0.055	-0.280	-0.054	-0.046	-0.072	-0.025	-0.121	-0.002
IV43	0.612	0.202	0.443	0.072	0.036	0.097	0.099	-0.010	-0.191	-0.067	0.142	0.007	-0.165	-0.114
IV18	-0.603	-0.031	0.400	-0.433	0.149	-0.212	0.061	-0.227	-0.089	-0.017	-0.055	-0.007	-0.086	0.009
IV26	0.548	0.202	0.366	0.140	0.043	0.183	0.080	0.010	-0.178	-0.088	0.230	0.066	-0.248	-0.174
IV71	-0.540	0.129	-0.023	-0.040	-0.224	0.199	0.027	-0.064	0.013	0.153	0.024	-0.042	-0.043	0.080
IV64	0.506	-0.205	0.152	0.147	0.370	-0.268	0.268	-0.080	-0.024	0.042	-0.229	0.039	0.011	0.053
IV63	0.493	-0.177	0.075	0.126	0.432	-0.258	-0.007	-0.086	-0.120	-0.031	-0.176	0.040	0.086	-0.026
IV40	0.167	-0.752	-0.262	0.318	-0.109	0.126	-0.026	0.212	0.153	-0.130	-0.077	0.045	-0.110	-0.072
IV23	0.111	-0.708	-0.305	0.288	-0.168	0.164	-0.041	0.224	0.157	-0.108	-0.077	0.048	-0.132	-0.082
IV51	-0.551	-0.602	0.066	0.084	0.147	-0.074	0.065	0.101	0.026	-0.021	0.123	0.056	-0.115	-0.037
IV13	0.180	0.583	-0.512	0.046	0.125	-0.024	0.195	0.150	-0.319	0.020	0.210	-0.039	-0.023	-0.100
IV27	0.124	0.563	-0.523	0.061	0.152	-0.064	0.186	0.118	-0.260	0.015	0.155	-0.046	0.033	-0.021
IV44	-0.207	0.453	0.269	-0.114	0.041	-0.029	0.113	-0.099	0.057	-0.107	0.044	0.127	0.297	-0.240
IV57	-0.139	0.363	0.002	0.066	0.155	-0.002	0.240	0.026	0.076	-0.050	-0.218	0.235	-0.149	-0.143
IV46	-0.014	-0.133	-0.449	-0.324	0.300	-0.140	0.165	-0.051	0.060	-0.129	-0.033	-0.139	0.417	-0.056
IV45	-0.079	0.065	0.433	0.081	-0.062	-0.035	0.221	-0.061	0.164	-0.192	0.083	0.058	0.263	-0.191
IV62	0.281	0.282	-0.416	-0.259	-0.303	-0.209	-0.089	-0.054	0.297	-0.076	-0.014	0.175	-0.101	0.081
IV68	0.320	-0.352	0.072	-0.556	-0.022	0.169	-0.079	0.101	-0.175	0.040	0.124	-0.086	0.073	-0.063
IV67	-0.346	0.148	0.023	0.543	0.248	-0.076	0.157	-0.052	-0.118	-0.055	0.022	-0.051	-0.076	0.191
IV69	0.254	-0.477	0.105	-0.491	-0.067	0.165	0.013	0.192	-0.155	0.085	0.080	-0.109	-0.017	-0.075
IV55	0.015	-0.140	0.163	0.361	0.008	0.088	0.081	0.067	-0.083	0.021	-0.174	0.198	0.253	-0.050
IV24	0.252	-0.013	0.066	-0.059	0.371	-0.299	-0.337	0.148	0.225	-0.214	0.116	0.253	0.036	0.019
IV66	0.031	-0.297	0.163	0.279	0.329	-0.188	-0.024	-0.127	-0.038	0.088	-0.120	-0.087	-0.094	-0.030
IV70	0.141	0.042	-0.032	0.039	0.316	0.217	0.028	-0.054	-0.023	0.085	-0.028	0.101	-0.220	-0.124
IV42	0.046	0.065	-0.052	-0.137	0.400	0.737	-0.070	-0.245	0.210	0.022	-0.065	0.100	0.035	0.165
IV25	0.046	0.065	-0.052	-0.137	0.400	0.737	-0.070	-0.245	0.210	0.022	-0.065	0.100	0.035	0.165
IV12	0.058	0.025	-0.053	-0.041	0.256	0.513	0.022	-0.193	0.139	-0.068	-0.008	0.145	0.005	-0.054
IV39	0.283	0.033	0.193	-0.164	-0.033	-0.048	0.604	0.184	0.336	0.097	-0.067	-0.036	-0.127	0.319
IV22	0.291	0.025	0.252	-0.225	-0.095	-0.016	0.519	0.189	0.303	0.134	-0.010	-0.109	-0.129	0.182
IV10	0.037	0.132	0.054	-0.087	0.165	-0.208	-0.416	0.232	0.313	-0.036	0.036	0.104	-0.022	-0.007
IV41	0.201	0.064	0.055	-0.129	0.294	-0.242	-0.388	0.221	0.258	-0.241	0.106	0.261	0.008	-0.008
IV21	0.183	-0.002	0.074	0.070	0.136	-0.069	0.368	0.040	0.132	-0.030	-0.064	0.077	-0.041	0.204
IV49	0.235	0.101	0.297	-0.196	-0.133	0.025	0.347	0.263	0.318	0.168	-0.094	-0.145	0.030	0.029
IV6	0.178	-0.176	-0.174	0.248	-0.194	-0.215	0.134	-0.496	0.155	0.183	0.063	0.078	0.056	-0.019
IV4	-0.003	0.301	0.082	-0.034	0.332	-0.124	-0.302	0.449	0.094	0.173	-0.157	-0.244	-0.092	0.109
IV17	-0.068	0.040	0.180	0.197	0.027	0.028	-0.128	0.087	0.247	0.557	0.478	0.043	0.269	-0.123
IV31	-0.017	0.041	0.210	0.053	-0.023	0.046	-0.079	0.148	0.258	0.484	0.434	0.028	0.306	-0.231
IV16	-0.007	0.090	0.121	0.181	-0.135	0.029	-0.036	-0.173	0.222	-0.457	0.305	-0.343	-0.008	0.258
IV30	0.052	0.105	0.164	0.184	-0.087	0.061	-0.070	-0.116	0.119	-0.383	0.322	-0.317	-0.159	0.234
IV14	0.285	0.314	0.140	0.022	-0.377	0.023	-0.290	-0.196	0.001	0.149	-0.456	-0.005	0.148	0.045
IV29	0.165	0.192	0.238	0.079	-0.096	0.044	-0.178	0.124	0.056	-0.035	-0.362	-0.244	0.168	-0.146
IV28	0.307	0.195	0.086	-0.047	-0.286	-0.025	-0.237	-0.310	-0.062	0.191	-0.330	0.075	0.099	0.102
IV35	-0.058	-0.026	0.191	0.013	-0.115	0.106	0.015	0.265	-0.294	-0.156	0.000	0.372	0.357	0.371
IV2	-0.244	0.200	-0.165	0.008	0.206	0.165	-0.113	0.288	-0.084	0.252	-0.205	-0.297	-0.138	0.117
IV47	-0.213	0.086	0.352	0.152	-0.266	0.117	-0.179	0.104	-0.108	0.076	-0.046	0.285	-0.432	0.102
IV19	-0.068	0.011	0.149	0.077	-0.085	0.105	0.027	0.278	-0.251	-0.165	-0.051	0.357	0.388	0.374
IV58	-0.232	-0.095	0.283	0.270	0.242	0.281	0.122	0.104	-0.085	-0.136	-0.043	-0.263	0.298	-0.180
IV72	0.263	0.091	0.073	0.159	0.210	0.063	-0.182	-0.011	0.021	0.024	0.079	-0.003	-0.036	0.335
IV20	0.274	0.005	0.137	-0.139	-0.025	-0.010	-0.145	-0.158	-0.225	0.071	0.090	0.054	-0.060	0.131
IV54	0.006	0.113	0.079	0.376	-0.273	-0.002	0.086	0.125	0.035	0.063	-0.138	-0.057	0.051	0.008
IV53	-0.258	0.191	-0.035	0.360	-0.156	0.148	-0.037	0.166	0.159	-0.067	-0.098	0.074	0.000	-0.048
IV52	-0.171	0.115	0.077	0.128	-0.040	0.076	-0.029	0.167	0.110	0.027	0.051	0.017	-0.102	0.076
IV56	-0.245	0.324	-0.107	0.176	0.154	-0.064	0.133	-0.107	0.282	0.009	-0.035	0.269	-0.216	-0.161
IV48	0.094	0.040	0.098	0.246	0.074	-0.037	-0.044	-0.137	0.069	0.173	-0.097	0.154	-0.120	-0.129
IV15	0.218	-0.022	0.221	0.211	0.144	-0.034	-0.025	-0.053	-0.074	-0.066	-0.241	-0.195	0.115	-0.244
IV36	0.164	0.053	0.026	-0.075	-0.181	0.030	-0.157	-0.166	-0.093	0.069	0.059	0.039	-0.037	0.119
IV32	0.124	0.170	0.059	-0.004	-0.111	0.149	0.043	0.095	-0.190	-0.055	0.026	0.034	-0.098	-0.334
IV65	-0.042	-0.058	0.084	0.243	0.226	-0.161	0.048	-0.062	-0.126	0.233	0.207	0.045	0.128	0.172
IV5	0.117	-0.020	0.050	-0.084	0.145	-0.066	-0.023	-0.055	-0.267	0.035	0.104	-0.043	-0.001	0.115
IV59	-0.050	-0.286	0.195	0.017	0.102	-0.106	-0.100	-0.098	-0.191	0.303	0.015	0.048	-0.169	0.194
IV7	-0.125	0.043	0.027	-0.182	-0.078	0.106	0.197	0.334	-0.216	-0.154	0.063	0.320	-0.011	-0.017
IV11	-0.128	0.221	-0.178	-0.006	0.221	-0.058	-0.020	0.263	-0.046	0.096	-0.101	-0.217	-0.061	0.082
IV8	-0.116	0.037	0.190	0.007	0.031	0.054	-0.113	0.026	-0.062	-0.252	-0.038	-0.340	-0.071	-0.017
IV60	-0.120	-0.032	-0.004	-0.017	0.053	-0.051	0.079	-0.019	-0.165	0.077	0.062	0.080	-0.045	0.083
IV1	0.039	-0.142	-0.268	-0.044	-0.011	0.094	0.203	-0.175	-0.061	0.265	0.022	-0.106	0.032	-0.053
IV38	0.145	0.049	-0.022	0.089	0.035	-0.034	-0.019	-0.046	-0.153	0.050	0.165	-0.076	-0.008	0.161
IV3	-0.047	-0.029	-0.165	0.185	-0.006	0.009	0.141	0.024	-0.128	0.116	-0.146	-0.028	0.112	0.201
IV50	0.244	0.054	0.050	0.205	-0.090	0.067	-0.092	-0.098	-0.117	-0.099	0.273	-0.288	0.070	0.011
IV61	0.064	0.018	0.103	-0.025	-0.058	0.124	0.048	0.111	-0.175	-0.069	0.117	0.088	-0.284	-0.290
IV33	0.005	0.055	-0.044	0.032	-0.101	-0.037	0.031	-0.157	0.192	-0.219	0.111	-0.111	0.125	0.128
IV9	-0.082	0.018	0.153	-0.049	-0.008	0.101	-0.162	0.216	0.026	0.120	-0.199	-0.302	0.024	-0.006
IV37	-0.013	-0.030	0.054	0.132	0.017	0.000	-0.105	0.006	0.006	0.356	0.217	-0.005	-0.071	0.198



	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
IV34	0.032	-0.155	0.031	-0.001	-0.095	0.042	-0.084	-0.014	0.071	0.078	-0.040	0.000	-0.031	0.008	-0.033
IV43	-0.001	0.002	0.074	0.080	0.042	-0.009	-0.115	-0.069	0.049	0.053	-0.005	0.042	-0.017	0.024	0.112
IV18	0.035	-0.198	0.077	0.019	-0.075	0.014	-0.092	-0.006	0.086	0.098	-0.061	0.031	-0.024	0.019	-0.006
IV26	0.013	-0.015	-0.019	0.088	0.097	-0.039	-0.120	-0.134	0.069	0.054	-0.018	0.120	-0.003	-0.038	0.080
IV71	-0.115	0.096	-0.060	0.178	0.132	0.050	-0.115	0.031	-0.028	-0.075	-0.122	0.078	-0.039	0.163	0.021
IV64	0.052	0.173	0.160	-0.082	-0.118	0.003	-0.069	0.061	-0.040	0.111	-0.001	0.004	-0.148	0.167	-0.089
IV63	0.052	0.145	0.038	-0.005	-0.195	0.081	-0.051	0.154	0.101	0.198	-0.049	-0.015	-0.135	0.207	-0.043
IV40	0.044	0.069	-0.100	-0.030	0.136	0.015	0.013	0.023	-0.013	0.027	0.117	0.025	0.032	-0.012	0.024
IV23	0.006	0.113	-0.152	-0.060	0.159	0.070	0.024	-0.007	0.018	0.049	0.103	0.002	-0.002	-0.030	0.022
IV51	0.012	0.010	0.046	-0.138	0.006	0.057	-0.143	0.040	0.072	-0.007	0.000	0.031	-0.034	0.052	0.053
IV13	-0.067	-0.013	0.048	0.058	0.025	0.053	0.076	0.042	0.060	-0.081	-0.092	-0.095	0.065	0.079	-0.038
IV27	-0.140	0.034	0.029	-0.097	0.078	0.038	0.057	0.027	-0.013	-0.147	-0.160	-0.042	0.067	0.070	0.070
IV44	0.153	0.099	-0.154	-0.045	0.228	0.047	0.186	-0.004	0.030	-0.060	0.217	0.094	0.077	0.089	0.052
IV57	0.087	0.273	-0.181	-0.066	-0.153	0.180	0.144	0.124	0.203	0.120	-0.024	-0.068	0.022	-0.137	0.134
IV46	0.244	0.034	0.062	0.164	0.105	-0.190	-0.106	-0.083	-0.088	-0.090	0.016	-0.060	-0.144	0.072	0.000
IV45	0.098	0.126	-0.028	0.009	0.161	-0.023	0.050	0.152	-0.007	-0.042	0.410	0.079	0.173	0.148	0.153
IV62	-0.069	-0.099	0.117	-0.144	-0.042	-0.051	-0.131	0.121	-0.012	0.228	0.155	-0.088	0.023	0.225	-0.062
IV68	0.115	0.048	0.085	0.110	-0.095	0.126	-0.041	0.200	0.026	0.032	-0.094	0.036	0.072	-0.017	0.227
IV67	-0.073	-0.042	-0.230	-0.046	0.132	-0.075	-0.097	-0.050	0.077	-0.212	0.048	-0.032	-0.104	-0.143	-0.116
IV69	0.087	0.045	0.013	0.103	-0.005	0.061	0.062	0.127	0.027	-0.092	-0.006	0.036	0.073	0.047	0.145
IV55	0.058	0.069	-0.089	0.165	0.094	0.099	-0.075	-0.068	-0.219	0.299	-0.336	-0.108	0.002	0.107	-0.101
IV24	0.029	-0.144	-0.156	0.233	-0.060	0.057	0.111	-0.084	-0.031	-0.184	-0.019	0.060	0.105	0.034	0.053
IV66	-0.209	0.117	0.121	0.049	0.039	-0.081	0.245	-0.082	-0.020	-0.124	0.016	0.206	-0.101	0.228	-0.181
IV70	-0.015	-0.098	0.227	-0.083	-0.155	0.084	-0.097	0.291	-0.208	-0.268	0.019	-0.092	0.287	-0.124	-0.089
IV42	-0.046	-0.062	0.004	0.049	0.031	-0.009	0.076	0.014	0.020	0.038	0.076	-0.026	-0.156	0.020	-0.021
IV25	-0.046	-0.062	0.004	0.049	0.031	-0.009	0.076	0.014	0.020	0.038	0.076	-0.026	-0.156	0.020	-0.021
IV12	-0.076	-0.061	0.052	-0.022	0.155	0.025	-0.122	-0.018	-0.003	0.111	-0.080	0.074	0.188	0.082	-0.038
IV39	-0.016	-0.108	-0.068	-0.032	-0.043	-0.051	-0.064	-0.111	-0.108	-0.099	0.031	0.008	0.058	-0.067	-0.064
IV22	-0.155	-0.063	-0.033	0.062	0.157	0.207	0.096	-0.131	0.026	-0.058	-0.113	-0.041	-0.052	0.012	-0.013
IV10	-0.110	-0.096	0.024	-0.043	0.082	-0.027	-0.052	-0.121	0.062	0.051	-0.092	0.077	-0.129	-0.157	-0.195
IV41	0.041	-0.124	-0.154	0.215	-0.061	0.062	0.091	-0.213	0.040	-0.070	-0.154	0.102	0.092	-0.060	0.149
IV21	0.225	-0.083	-0.072	-0.104	-0.259	-0.277	-0.244	-0.003	-0.165	-0.090	0.265	0.061	0.132	-0.147	-0.029
IV49	-0.124	-0.012	-0.057	0.030	0.186	0.124	0.152	0.003	0.067	0.074	-0.179	-0.045	-0.081	0.011	-0.042
IV6	-0.023	-0.165	0.140	0.167	-0.124	0.356	0.196	-0.034	0.086	-0.163	0.086	-0.059	-0.085	-0.030	0.132
IV4	0.074	0.143	0.106	0.006	0.097	0.140	-0.035	0.108	0.029	0.050	0.175	0.106	-0.104	-0.007	-0.016
IV17	-0.028	0.115	0.043	-0.130	-0.207	-0.112	-0.064	-0.040	-0.087	0.033	0.026	-0.061	-0.050	0.014	-0.018
IV31	-0.038	0.115	0.090	-0.131	-0.113	-0.026	-0.095	0.073	-0.081	0.131	-0.015	0.073	-0.018	-0.044	-0.142
IV16	0.094	0.305	0.219	0.156	-0.076	-0.071	0.102	0.124	-0.020	0.032	-0.121	0.019	-0.003	-0.088	-0.036
IV30	-0.027	0.245	0.135	0.062	-0.029	-0.034	-0.085	0.059	-0.039	-0.026	-0.114	0.075	-0.124	0.232	0.086
IV14	-0.101	0.127	-0.197	0.131	-0.018	-0.066	-0.149	-0.052	-0.100	-0.068	0.036	0.119	-0.055	-0.049	0.029
IV29	-0.157	-0.234	-0.058	-0.147	0.058	-0.288	0.293	0.146	0.042	0.048	-0.008	-0.169	-0.102	-0.118	0.073
IV28	0.050	0.287	-0.111	0.182	0.035	-0.033	-0.302	-0.013	-0.014	-0.168	0.045	0.097	-0.017	-0.043	0.123
IV35	-0.164	0.016	0.319	-0.034	-0.019	0.082	0.049	-0.055	0.144	-0.086	0.125	-0.012	0.017	0.024	-0.052
IV2	0.063	0.113	0.140	0.084	-0.122	0.040	0.051	-0.134	-0.049	0.133	0.147	0.192	0.084	-0.008	0.071
IV47	-0.052	0.105	-0.112	-0.057	-0.292	0.097	0.243	0.116	-0.070	0.062	0.028	-0.189	0.015	0.003	0.055
IV19	-0.163	0.044	0.276	-0.041	-0.060	0.164	0.037	-0.084	0.085	-0.038	0.105	-0.015	0.017	0.032	-0.082
IV58	0.122	0.039	-0.202	-0.083	-0.220	0.262	-0.060	-0.144	0.022	-0.185	-0.196	-0.005	-0.032	-0.166	0.128
IV72	0.214	-0.032	-0.298	-0.152	-0.173	-0.184	-0.023	0.102	0.130	-0.173	-0.103	-0.115	0.059	0.093	0.020
IV20	0.508	0.073	0.018	-0.381	0.199	0.138	0.155	-0.025	-0.154	-0.052	-0.050	-0.017	-0.090	-0.026	-0.058
IV54	0.396	-0.226	0.155	0.114	0.002	0.064	-0.129	0.152	0.105	-0.093	-0.107	0.055	-0.100	0.093	0.002
IV53	0.375	-0.354	0.209	0.124	0.047	-0.017	-0.119	0.029	0.022	0.043	-0.129	-0.027	-0.193	0.036	0.075
IV52	0.330	-0.302	0.092	0.074	0.249	-0.142	0.074	0.026	0.005	0.019	0.064	0.027	0.163	0.252	0.075
IV56	0.101	0.353	0.009	-0.101	0.078	0.017	0.111	-0.078	0.088	0.167	-0.004	0.070	0.067	0.142	0.114
IV48	-0.100	-0.054	0.402	-0.003	0.215	0.011	-0.273	0.064	0.014	-0.066	-0.218	0.186	0.252	-0.207	0.019
IV15	-0.165	-0.269	0.279	-0.184	0.029	-0.261	0.275	0.115	-0.034	0.029	-0.010	-0.062	0.017	0.004	0.183
IV36	0.366	-0.168	0.002	-0.398	0.028	0.235	0.272	-0.085	-0.201	-0.039	-0.056	0.259	-0.072	0.028	-0.166
IV32	0.140	-0.008	0.047	0.374	-0.179	0.013	0.098	-0.254	-0.099	0.063	0.143	-0.171	0.013	0.063	-0.299
IV65	0.032	-0.146	-0.262	0.336	0.202	0.084	0.024	0.298	-0.223	0.086	0.171	-0.129	0.028	-0.076	0.011
IV5	0.205	0.131	-0.108	-0.096	0.396	-0.087	-0.108	-0.224	-0.009	0.299	-0.014	-0.321	0.044	-0.177	-0.023
IV59	-0.025	0.122	0.196	0.136	0.361	-0.237	0.148	-0.111	0.204	-0.041	0.037	-0.047	0.146	-0.083	0.032
IV7	-0.018	0.105	-0.121	-0.134	-0.044	-0.492	-0.050	0.195	-0.012	0.042	-0.155	0.254	-0.192	-0.034	0.096
IV11	0.066	0.106	0.170	-0.003	0.088	0.267	-0.045	0.048	-0.138	0.030	0.231	0.116	-0.193	-0.169	0.241
IV8	-0.204	-0.088	-0.036	-0.117	-0.105	0.057	-0.127	-0.205	-0.432	0.110	0.119	-0.153	0.162	0.161	0.029
IV60	-0.150	-0.027	-0.213	0.230	0.103	-0.061	0.278	0.323	-0.413	-0.018	-0.135	0.322	-0.048	0.031	-0.114
IV1	0.137	-0.018	-0.074	-0.009	-0.208	-0.205	0.183	-0.173	0.301	-0.018	0.005	0.198	-0.012	-0.017	-0.034
IV38	-0.040	-0.302	-0.198	0.152	-0.086	0.141	-0.124	0.320	0.319	0.373	0.118	0.024	-0.043	-0.036	-0.028
IV3	0.112	-0.131	-0.010	0.134	-0.250	-0.082	0.136	-0.267	-0.093	0.362	-0.064	0.319	0.296	0.020	0.134
IV50	-0.240	-0.199	-0.208	-0.217	0.073	0.124	-0.078	-0.094	0.241	0.102	0.165	0.315	0.070	0.011	-0.061
IV61	0.092	-0.036	0.110	0.270	-0.069	-0.125	-0.003	-0.109	0.007	-0.086	0.261	0.062	-0.333	-0.110	-0.201
IV33	0.138	0.182	0.224	0.171	-0.089	-0.114	0.282	0.103	-0.007	0.200	-0.028	-0.018	0.134	-0.450	-0.111
IV9	0.201	0.173	-0.103	0.107	-0.036	-0.041	0.028	0.152	0.304	-0.161	-0.047	-0.085	0.342	0.204	-0.380
IV37	-0.023	-0.004	0.052	0.087	-0.126	-0.224	0.103	-0.193	-0.015	-0.066	-0.001	-0.243	-0.087	0.166	0.365

## APPENDIX 12 – ROTATED COMPONENT MATRIX

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
IV13	0.922	0.018	0.081	-0.016	-0.029	-0.073	-0.028	-0.032	-0.101	-0.049	0.104	-0.066	-0.038	-0.008
IV27	0.895	0.003	0.152	-0.035	-0.038	-0.038	-0.015	-0.034	-0.051	-0.055	0.124	-0.107	-0.040	-0.002
IV23	-0.333	-0.845	-0.068	-0.001	-0.032	-0.199	-0.053	-0.058	0.030	-0.129	-0.061	0.010	-0.092	-0.068
IV40	-0.358	-0.838	-0.096	0.078	-0.043	-0.219	-0.072	-0.025	0.031	-0.136	-0.084	-0.042	-0.066	-0.056
IV18	-0.396	0.807	-0.041	-0.083	-0.062	-0.230	-0.039	-0.048	0.055	-0.124	-0.007	0.007	-0.105	-0.029
IV34	-0.386	0.806	0.054	-0.069	-0.054	-0.221	-0.063	-0.045	0.079	-0.139	0.003	0.044	-0.077	-0.083
IV68	-0.053	-0.001	-0.879	0.067	0.052	0.007	0.030	0.032	0.035	-0.004	0.000	-0.067	-0.001	0.008
IV69	-0.153	-0.128	-0.769	0.007	-0.015	-0.080	0.138	-0.027	0.068	-0.064	-0.017	-0.077	-0.094	0.001
IV67	0.057	0.030	0.682	-0.042	-0.041	-0.108	-0.088	-0.083	0.355	-0.118	0.058	0.018	0.010	0.027
IV63	0.022	-0.042	-0.104	0.867	0.003	0.039	-0.078	0.137	0.008	-0.022	0.007	-0.030	-0.022	-0.010
IV64	-0.049	-0.071	0.007	0.858	-0.033	0.018	0.175	-0.029	-0.016	-0.020	0.010	-0.094	-0.009	0.018
IV66	-0.225	-0.070	0.261	0.430	-0.032	-0.130	-0.014	0.019	0.114	-0.046	0.033	-0.105	0.007	-0.016
IV71	-0.042	0.186	0.120	-0.381	0.078	0.089	0.011	-0.275	0.051	0.019	0.037	0.041	0.009	-0.017
IV55	-0.074	-0.170	0.111	0.287	0.036	0.099	0.053	-0.027	0.242	0.125	-0.230	0.069	-0.072	0.141
IV25	-0.033	0.012	-0.012	-0.017	0.952	0.019	0.003	-0.007	0.038	-0.007	0.059	-0.022	0.013	0.018
IV42	-0.033	0.012	-0.012	-0.017	0.952	0.019	0.003	-0.007	0.038	-0.007	0.059	-0.022	0.013	0.018
IV12	0.044	-0.049	-0.028	-0.008	0.625	-0.051	-0.010	-0.005	-0.006	-0.014	-0.129	-0.044	-0.041	-0.033
IV14	-0.054	-0.004	0.066	-0.030	-0.017	0.897	0.025	-0.004	-0.072	-0.014	0.003	0.071	-0.051	-0.007
IV28	-0.046	0.011	-0.072	0.061	-0.026	0.872	-0.066	-0.040	-0.059	-0.053	-0.005	-0.004	-0.010	-0.018
IV51	-0.478	-0.035	0.019	-0.008	-0.133	-0.540	-0.181	-0.120	0.211	0.014	0.006	-0.004	-0.123	0.013
IV22	0.017	0.009	-0.092	0.025	-0.004	-0.033	0.896	-0.004	-0.007	-0.044	-0.011	0.012	-0.005	0.006
IV49	-0.002	0.008	-0.107	0.022	0.001	0.042	0.782	-0.006	-0.005	0.104	0.029	0.041	-0.006	-0.023
IV39	-0.030	0.008	0.023	0.046	-0.009	-0.006	0.777	-0.021	-0.070	-0.031	-0.031	-0.043	-0.004	0.011
IV41	0.013	0.007	-0.076	0.015	-0.004	0.010	-0.001	0.904	0.014	-0.037	0.011	0.009	0.006	-0.015
IV24	0.009	-0.027	-0.047	0.138	-0.008	-0.025	-0.041	0.843	-0.016	-0.045	-0.027	-0.048	-0.018	0.010
IV10	-0.127	0.060	0.191	-0.050	-0.007	0.002	0.045	0.546	-0.169	0.193	0.178	-0.052	-0.012	0.005
IV58	-0.039	0.018	0.020	0.017	0.069	-0.082	-0.028	-0.023	0.896	0.085	0.026	0.012	0.015	0.023
IV62	0.209	-0.041	-0.016	0.000	-0.021	0.132	0.033	0.064	-0.834	0.000	-0.051	-0.018	-0.003	-0.061
IV17	-0.022	0.003	0.063	-0.022	-0.009	-0.026	-0.032	0.008	0.064	0.910	0.002	0.049	-0.016	-0.018
IV31	-0.047	0.016	-0.059	-0.021	-0.015	-0.039	0.058	-0.012	0.009	0.894	0.026	-0.006	-0.010	-0.009
IV4	0.035	0.064	0.044	0.122	-0.017	0.046	0.065	0.227	-0.050	0.102	0.779	0.034	-0.009	0.002
IV11	0.137	0.008	0.005	-0.024	-0.032	-0.025	-0.011	-0.044	0.064	-0.047	0.740	-0.050	-0.010	0.002
IV2	0.077	0.049	0.034	-0.104	0.104	-0.018	-0.072	-0.097	0.057	0.007	0.661	0.043	-0.042	-0.029
IV47	-0.144	0.052	0.053	-0.106	-0.063	0.023	-0.056	-0.042	-0.008	0.009	-0.010	0.857	0.003	0.105
IV46	0.118	0.031	-0.121	0.098	0.065	-0.082	-0.105	0.044	-0.022	-0.087	0.032	-0.779	-0.019	-0.087
IV57	0.220	0.114	0.179	0.120	0.065	-0.007	0.054	0.007	0.125	-0.107	0.140	0.455	-0.053	-0.118
IV16	-0.029	-0.003	0.050	-0.027	-0.014	-0.020	-0.009	-0.008	0.035	-0.017	-0.031	-0.005	0.926	0.000
IV30	0.020	-0.006	0.047	0.094	0.016	0.018	0.020	-0.022	0.016	-0.047	-0.004	0.029	0.702	-0.047
IV33	-0.040	0.005	0.001	-0.125	-0.013	-0.037	-0.031	0.018	-0.074	0.046	-0.013	-0.012	0.611	0.034
IV35	-0.015	0.024	-0.041	-0.015	-0.003	-0.023	-0.011	-0.007	0.013	-0.022	-0.025	0.046	-0.005	0.905
IV19	0.014	-0.009	0.030	0.026	0.013	-0.003	0.002	0.004	0.049	-0.001	0.012	0.061	-0.008	0.890
IV53	-0.028	-0.004	0.200	-0.159	0.050	-0.063	-0.083	0.007	0.036	0.011	0.069	0.017	0.033	0.015
IV54	0.007	-0.056	0.062	0.044	-0.173	0.111	0.053	-0.125	0.086	0.005	0.017	0.008	0.048	0.041
IV52	-0.037	0.006	0.056	-0.193	0.052	-0.191	0.022	0.067	-0.154	-0.053	0.060	-0.004	-0.025	-0.022
IV29	-0.021	-0.009	0.054	-0.041	0.001	0.189	0.099	0.027	0.018	-0.006	0.030	0.079	-0.031	-0.035
IV15	0.006	0.003	-0.016	0.238	-0.003	-0.083	-0.043	-0.049	0.058	-0.044	-0.041	-0.038	-0.007	-0.014
IV50	0.057	-0.128	0.093	-0.047	-0.015	0.032	-0.001	-0.012	0.061	0.051	-0.052	-0.064	0.053	0.000
IV38	0.049	0.098	-0.098	0.140	0.040	-0.044	-0.059	-0.013	-0.135	-0.001	0.024	0.140	-0.011	-0.011
IV45	-0.179	0.021	-0.013	0.018	-0.059	0.001	0.053	-0.059	0.049	0.080	-0.069	-0.013	0.109	0.097
IV44	0.114	0.286	0.141	-0.143	0.044	0.082	0.025	0.071	0.079	0.065	0.007	-0.033	-0.044	0.032
IV56	0.130	0.025	0.387	0.091	0.104	-0.096	-0.029	0.022	-0.128	0.032	0.110	0.248	0.042	-0.228
IV7	0.055	0.027	-0.083	-0.067	-0.056	-0.059	-0.027	-0.060	-0.015	-0.006	-0.099	0.057	-0.044	0.127
IV6	-0.003	-0.092	0.033	0.107	-0.096	0.063	0.025	-0.072	-0.041	-0.010	-0.239	-0.012	0.019	-0.050
IV36	-0.013	0.014	-0.029	-0.040	0.006	0.035	-0.001	0.005	-0.059	0.017	-0.026	0.054	-0.025	0.001
IV20	0.015	0.013	-0.158	0.127	-0.008	0.066	-0.036	-0.023	0.006	-0.021	0.007	0.045	0.020	-0.012
IV61	-0.072	-0.008	-0.017	-0.023	-0.010	-0.039	-0.040	-0.023	0.003	-0.032	0.061	0.018	-0.012	-0.024
IV32	0.155	0.009	-0.051	0.001	0.000	0.047	-0.011	0.012	0.001	0.025	-0.092	0.079	-0.026	0.006
IV26	0.178	-0.070	-0.116	0.208	0.093	0.158	0.193	0.137	0.118	0.003	-0.120	0.185	0.098	-0.073
IV43	0.168	0.019	-0.204	0.330	0.042	0.215	0.243	0.091	0.078	0.001	-0.092	0.164	0.122	0.001
IV21	-0.073	-0.022	0.103	0.149	-0.016	0.021	0.128	-0.013	-0.018	0.003	-0.017	-0.073	-0.007	-0.013
IV72	0.130	-0.046	0.062	0.176	0.152	0.117	-0.069	0.234	0.098	0.025	-0.106	0.147	0.084	-0.058
IV48	-0.012	0.012	0.083	0.065	0.009	0.097	-0.019	0.017	-0.011	0.078	-0.003	0.012	-0.018	-0.014
IV70	0.218	-0.001	-0.129	0.085	0.259	-0.130	-0.126	-0.020	0.042	0.023	0.037	0.165	-0.090	-0.061
IV60	0.036	0.034	0.011	-0.033	-0.013	-0.019	0.028	-0.010	0.002	-0.051	-0.025	0.030	0.018	-0.067
IV65	0.002	0.000	0.060	0.071	-0.021	-0.041	-0.053	0.041	0.070	0.114	0.044	0.008	-0.069	-0.010
IV37	0.032	0.011	-0.015	-0.021	0.002	0.013	-0.011	0.023	0.004	0.224	0.008	0.120	0.007	-0.013
IV59	-0.263	0.021	-0.005	0.000	-0.061	-0.061	-0.012	-0.052	-0.038	-0.088	0.035	-0.012	-0.023	0.106
IV8	-0.071	0.087	0.040	-0.066	-0.015	-0.041	-0.042	-0.040	0.077	-0.055	0.070	0.042	0.067	-0.043
IV1	0.041	-0.031	-0.027	-0.005	0.054	-0.051	-0.025	-0.200	0.060	0.032	-0.115	-0.178	-0.099	-0.180
IV5	0.020	0.014	0.010	0.058	-0.013	-0.009	-0.006	-0.037	0.011	-0.041	0.009	-0.096	-0.024	-0.032
IV3	0.019	-0.027	0.032	0.026	-0.030	0.005	-0.038	-0.033	0.035	-0.042	0.038	-0.011	-0.024	0.056
IV9	-0.041	0.021	-0.081	-0.018	-0.032	0.058	0.023	-0.028	0.089	0.017	0.072	0.037	0.020	-0.026





## APPENDIX 13 – LIST OF VARIABLES PER COMPONENT

### Factor 1

Survey Question	Name	Variable Code	Strength
Q10	Walk	IV13	0.922
Q10	Walk and Vehicle	IV18	-0.396
Q10	Vehicle	IV23	-0.333
Q12	Walk	IV27	0.895
Q12	Walk and Vehicle	IV34	-0.386
Q12	Vehicle	IV40	-0.358
Q18	Household Car	IV51	-0.478

### Factor 2

Survey Question	Name	Variable Code	Strength
Q10	Walk and Vehicle	IV18	0.807
Q10	Vehicle	IV23	-0.845
Q12	Walk and Vehicle	IV34	0.806
Q12	Vehicle	IV40	-0.838

### Factor 3

Survey Question	Name	Variable Code	Strength
Q28	Selection of Vegetables by Someone	IV56	0.387
Q36	Grocery for 19-60 years old	IV67	0.682
Q36	Grocery for over 60 years old	IV68	-0.879
Q39	Age	IV69	-0.769

### Factor 4

Survey Question	Name	Variable Code	Strength
Q13	Commute	IV43	0.330
Q33	Food Run Out	IV63	0.867
Q33	No Money and No Food	IV64	0.858
Q36	Grocery for 6 to 18 years old	IV66	0.430
Q40	Educational Level	IV71	-0.381

Factor 5

Survey Question	Name	Variable Code	Strength
Q8	Other Location for Grocery	IV12	0.625
Q10	Walk, Bike and Vehicle	IV25	0.952
Q12	Walk, Bike and Vehicle	IV42	0.952

Factor 6

Survey Question	Name	Variable Code	Strength
Q10	Walk and Public Transportation	IV14	0.897
Q12	Walk and Public Transportation	IV28	0.872
Q18	Household Car	IV51	-0.540

Factor 7

Survey Question	Name	Variable Code	Strength
Q10	Public Transportation and Vehicle	IV22	0.896
Q12	Ridesharing and Vehicle	IV39	0.777
Q12	Ridesharing	IV49	0.782

Factor 8

Survey Question	Name	Variable Code	Strength
Q8	Neighborhood Market	IV10	0.546
Q10	Vehicle and Ridesharing	IV24	0.843
Q12	Vehicle and Ridesharing	IV41	0.904

Factor 9

Survey Question	Name	Variable Code	Strength
Q31	Grocery Weekly Spent \$ 100-150	IV58	0.896
Q31	Grocery Weekly Less than \$100	IV62	-0.834
Q36	Grocery for 19-60 years old	IV67	0.355

Factor 10

Survey Question	Name	Variable Code	Strength
Q10	Walk, Public Transp, and Vehicle	IV17	0.910
Q12	Walk, Public Transp, and Vehicle	IV31	0.894

## Factor 11

Survey Question	Name	Variable Code	Strength
Q4	Frequency Neighborhood Markets	IV2	0.661
Q5	Frequency of Specific Markets	IV4	0.779
Q8	Location Pref - Neighborhood Market and Farmers	IV11	0.740

## Factor 12

Survey Question	Name	Variable Code	Strength
Q16	Ideal Transp: Satisfied with current situation	IV46	-0.779
Q16	Ideal Transp: Walk	IV47	0.857
Q28	Adaptability of Household Meals	IV57	0.455

## Factor 13

Survey Question	Name	Variable Code	Strength
Q10	Walk, Public Transp, Ridesharing, Vehicle	IV16	0.926
Q12	Walk, Public Transp, Ridesharing, Vehicle	IV30	0.702
Q12	Walk and Vehicle	IV33	0.611

## Factor 14

Survey Question	Name	Variable Code	Strength
Q10	Walk, Vehicle, and Ridesharing	IV19	0.890
Q10	Walk, Vehicle, and Ridesharing	IV35	0.905

## Factor 15

Survey Question	Name	Variable Code	Strength
Q19	Ownership of Smartphone	IV52	0.484
Q20	Comfortability in using Ridesharing	IV53	0.798
Q21	Use of Ridesharing	IV54	0.701

## Factor 16

Survey Question	Name	Variable Code	Strength
Q10	Walk, Public Transp and Ridesharing	IV15	0.768
Q12	Walk, Public Transp and Ridesharing	IV29	0.823
Q40	Educational Level	IV71	-0.301

Factor 17

Survey Question	Name	Variable Code	Strength
Q11	Travel Time to Store	IV26	0.382
Q12	Ridesharing	IV38	0.603
Q13	Travel Time from Store	IV43	0.330
Q16	Ideal Transp: Satisfied with current situation	IV46	-0.303
Q16	Ideal Vehicle	IV50	0.795

Factor 18

Survey Question	Name	Variable Code	Strength
Q15	Effects of Transp on Quantity of Food	IV44	0.734
Q15	Effects of Transp on Type of Food	IV45	0.801
Q28	Selection of Vegetables by Someone	IV56	0.401

Factor 19

Survey Question	Name	Variable Code	Strength
Q8	Location Pref: Grocery Store	IV6	-0.736
Q8	Location Pref: Grocery Store and Farmers	IV7	0.842

Factor 20

Survey Question	Name	Variable Code	Strength
Q10	Public Transportation	IV20	0.780
Q12	Public Transportation	IV36	0.841

Factor 21

Survey Question	Name	Variable Code	Strength
Q11	Travel Time to Store	IV26	0.424
Q12	Walk and Ridesharing	IV32	0.721
Q13	Travel Time from Store	IV43	0.360
Q31	Grocery Weekly Spent \$ 250-300	IV61	0.744

Factor 22

Survey Question	Name	Variable Code	Strength
Q10	Public Transp, Ridesharing, and Vehicle	IV21	0.776
Q12	Ridesharing and Vehicle	IV39	0.483
Q38	Gender	IV70	0.374
Q41	Race	IV72	0.339

## Factor 23

Survey Question	Name	Variable Code	Strength
Q16	Ideal: Public Transportation	IV48	0.794
Q31	Grocery Weekly Spent \$ 150-200	IV59	0.344
Q38	Gender	IV70	0.423

## Factor 24

Survey Question	Name	Variable Code	Strength
Q31	Grocery Weekly Spent \$ 200-250	IV60	0.736
Q36	Grocery for 0-5 years old	IV65	0.722

## Factor 25

Survey Question	Name	Variable Code	Strength
Q12	Public Transp and Vehicle	IV37	0.685
Q31	Grocery Weekly Spent \$ 150-200	IV59	0.489

## Factor 26

Survey Question	Name	Variable Code	Strength
Q4	Freq: Grocery Store	IV1	0.426
Q8	Location Pref: Grocery Store and NM	IV8	-0.769

## Factor 27

Survey Question	Name	Variable Code	Strength
Q8	Location Pref: Farmers Market	IV5	0.789
Q31	Grocery Weekly Spent \$ 150-200	IV59	0.316

## Factor 28

Survey Question	Name	Variable Code	Strength
Q4	Freq: Grocery Store	IV1	0.341
Q4	Freq: Neighborhood Market	IV2	0.361
Q4	Freq: Other	IV3	0.836

## Factor 29

Survey Question	Name	Variable Code	Strength
Q8	Location Pref: Grocery Store	IV6	-0.312

Q8

Location Pref: Grocery Store, NM, and Farmers

IV9

0.874



## APPENDIX 14 – COMPONENT TRANSFORMATION MATRIX

Component	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1	0.255	-0.367	-0.300	0.439	0.058	0.326	0.270	0.208	-0.167	-0.003	-0.136	-0.057	0.054	-0.035	-0.087	0.192	0.237	-0.085	-0.088	0.187	0.158	0.182	0.100	-0.068	0.019	0.026	0.092	-0.044	-0.054
2	0.603	0.404	0.315	-0.156	0.090	0.317	0.083	0.086	-0.144	0.073	0.227	0.159	0.105	-0.020	0.150	0.086	0.053	0.212	0.080	0.038	0.091	0.019	-0.016	-0.081	-0.101	-0.039	0.015	-0.010	0.008
3	-0.448	0.368	-0.072	0.155	-0.057	0.108	0.287	0.079	0.294	0.154	-0.095	0.307	0.106	0.159	0.041	0.193	0.119	0.281	0.101	0.074	0.144	0.026	0.147	0.057	0.118	-0.181	0.087	-0.146	0.106
4	0.051	-0.434	0.559	0.202	-0.109	-0.008	-0.193	-0.089	0.270	0.115	-0.041	0.199	0.146	0.043	0.331	0.099	0.156	0.018	-0.157	-0.088	-0.006	0.022	0.176	0.112	0.120	-0.031	-0.036	0.104	-0.030
5	0.113	0.189	0.121	0.437	0.410	-0.344	-0.123	0.330	0.257	-0.017	0.293	-0.174	-0.122	-0.110	-0.199	0.010	-0.049	0.016	0.022	-0.099	-0.073	0.143	0.109	0.122	0.070	0.000	0.114	-0.024	0.050
6	0.028	-0.226	-0.184	-0.263	0.774	0.036	-0.002	-0.276	0.232	0.045	-0.034	0.137	0.032	0.090	0.103	0.008	0.050	-0.033	0.143	0.020	0.157	-0.019	0.005	-0.094	-0.009	-0.075	-0.043	0.036	0.083
7	0.192	0.055	0.073	0.142	-0.058	-0.265	0.550	-0.451	0.134	-0.131	-0.182	-0.116	-0.042	0.003	0.012	-0.143	-0.082	0.215	0.049	-0.160	0.064	0.284	-0.010	0.050	-0.093	0.137	-0.039	0.142	-0.184
8	0.119	-0.317	-0.142	-0.105	-0.262	-0.243	0.257	0.246	0.064	0.133	0.406	0.083	-0.174	0.278	0.192	0.055	-0.060	-0.087	0.384	-0.162	0.097	0.027	-0.113	-0.038	-0.050	-0.101	0.000	-0.003	0.190
9	-0.288	-0.159	0.183	-0.109	0.231	-0.036	0.374	0.311	-0.234	0.276	0.011	-0.058	0.209	-0.291	0.125	-0.013	-0.188	0.135	-0.170	-0.151	-0.238	0.086	-0.024	-0.197	-0.113	0.038	-0.220	-0.074	0.000
10	0.006	0.069	-0.047	-0.009	-0.001	0.171	0.156	-0.247	-0.047	0.530	0.200	0.075	-0.444	-0.154	-0.015	-0.050	-0.057	-0.172	-0.177	0.066	-0.065	-0.025	0.139	0.174	0.323	0.257	0.035	0.128	0.126
11	0.217	0.012	-0.129	-0.205	-0.059	-0.391	-0.064	0.127	-0.017	0.462	-0.193	-0.040	0.331	-0.024	-0.091	-0.303	0.321	0.064	0.014	0.091	0.116	0.010	-0.031	0.121	0.225	0.011	0.091	-0.154	-0.165
12	-0.021	-0.046	0.097	0.068	0.146	0.023	-0.127	0.285	-0.231	0.039	-0.326	0.303	-0.343	0.368	0.052	-0.255	-0.263	0.151	0.159	0.024	0.056	0.048	0.137	0.065	-0.055	0.257	0.020	-0.030	-0.273
13	0.060	0.019	-0.076	0.026	0.021	0.200	-0.099	0.022	0.215	0.364	-0.147	-0.497	-0.026	0.435	0.048	0.199	-0.025	0.229	-0.095	-0.068	-0.262	-0.067	-0.240	0.059	-0.204	0.046	0.038	0.117	-0.003
14	-0.091	0.066	0.130	-0.025	0.129	0.098	0.198	0.009	-0.147	-0.200	0.140	0.038	0.290	0.431	0.008	-0.211	0.096	-0.300	-0.009	0.138	-0.389	0.254	-0.163	0.196	0.279	0.025	0.122	0.108	0.060
15	-0.076	0.013	-0.158	0.064	-0.053	-0.034	-0.164	0.035	0.103	-0.042	0.078	-0.092	0.085	-0.200	0.524	-0.188	-0.206	0.182	-0.018	0.456	0.100	0.259	-0.147	-0.092	-0.027	0.218	0.260	0.114	0.172
16	0.033	-0.212	0.003	0.222	-0.080	0.249	-0.062	-0.178	0.101	0.125	0.191	0.128	0.356	0.008	-0.424	-0.331	-0.340	0.221	0.185	-0.074	-0.033	-0.165	-0.023	-0.138	0.007	0.113	0.122	-0.073	0.143
17	0.009	0.139	-0.140	0.123	0.010	-0.214	-0.069	-0.183	-0.248	0.079	0.210	-0.162	0.273	0.356	0.165	0.150	-0.252	-0.092	-0.172	0.028	0.150	-0.084	0.489	-0.256	0.087	0.009	-0.120	0.003	-0.116
18	-0.021	0.057	-0.162	-0.044	0.038	0.218	0.048	0.213	0.025	-0.151	0.008	-0.115	0.182	-0.017	0.187	-0.194	-0.095	-0.024	-0.211	-0.499	0.418	-0.149	-0.007	0.413	0.104	0.117	-0.006	0.163	0.082
19	-0.033	-0.202	0.139	-0.197	0.064	-0.012	0.201	-0.039	-0.120	-0.214	0.077	-0.302	-0.093	-0.023	0.072	0.032	0.057	0.282	0.086	0.133	-0.106	-0.368	0.318	0.224	0.075	0.024	0.440	-0.274	0.007
20	0.079	-0.013	-0.145	0.065	0.000	-0.059	0.156	0.052	0.215	-0.072	0.229	0.230	-0.114	0.139	0.045	-0.367	0.125	0.034	-0.550	0.182	-0.109	-0.273	-0.010	-0.004	-0.356	-0.122	-0.081	-0.113	-0.110
21	0.095	-0.084	0.015	-0.077	0.033	-0.268	0.108	0.102	-0.006	-0.107	-0.016	0.219	0.133	0.045	-0.229	0.435	-0.212	0.168	-0.167	0.315	0.081	-0.258	-0.249	0.213	0.132	0.281	-0.141	0.246	0.066
22	0.071	0.010	-0.276	0.141	0.020	-0.063	-0.163	-0.205	-0.185	0.020	0.055	0.211	0.140	-0.077	0.178	0.162	0.049	0.077	0.110	-0.128	-0.300	0.119	0.045	0.466	-0.263	0.195	-0.189	-0.373	0.135
23	-0.010	0.089	0.008	0.049	0.009	-0.096	0.006	0.030	0.021	-0.132	-0.061	0.055	-0.036	0.105	0.056	-0.005	0.414	0.037	-0.045	-0.249	-0.065	-0.161	-0.033	-0.450	0.082	0.604	0.041	-0.082	0.297
24	-0.163	0.050	-0.036	0.224	0.096	-0.138	-0.015	-0.111	-0.330	0.152	0.090	0.185	0.074	-0.088	0.068	0.057	0.197	-0.015	0.104	-0.145	-0.019	-0.240	-0.144	0.008	-0.280	-0.086	0.442	0.468	-0.185
25	-0.214	-0.143	0.065	-0.071	0.033	0.002	-0.178	-0.146	-0.281	-0.024	0.351	-0.039	-0.152	0.154	-0.190	0.025	0.220	0.432	-0.246	-0.071	0.295	0.365	-0.209	0.013	0.073	-0.043	-0.026	-0.096	-0.039
26	-0.156	-0.009	0.004	-0.006	-0.021	0.115	-0.008	0.088	0.041	-0.025	0.209	-0.185	0.048	-0.041	-0.062	-0.175	0.334	0.139	0.342	0.244	0.002	-0.072	0.276	0.123	-0.133	0.183	-0.481	0.375	-0.094
27	0.143	-0.053	-0.167	-0.216	-0.072	-0.081	-0.075	0.096	-0.061	-0.056	-0.176	0.133	-0.021	0.017	-0.160	-0.043	0.005	0.245	-0.173	-0.103	-0.231	0.239	0.416	-0.017	-0.062	-0.204	0.117	0.392	0.442
28	0.100	0.019	-0.025	0.343	0.074	-0.074	0.003	-0.078	-0.270	-0.039	-0.160	-0.072	-0.137	0.006	0.209	-0.197	0.022	0.237	0.078	0.036	-0.073	-0.300	-0.217	-0.032	0.357	-0.370	-0.310	0.027	0.281
29	0.076	-0.038	-0.338	-0.078	-0.039	0.100	-0.068	0.066	0.164	-0.145	0.165	0.143	-0.013	-0.124	0.130	0.101	-0.020	0.260	0.020	-0.198	-0.356	0.007	-0.007	-0.141	0.421	-0.006	0.000	0.100	-0.521



## APPENDIX 15 –COMPONENT SCORE COEFFICIENT MATRIX

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
IV1	-0.003	0.027	0.023	-0.008	0.014	-0.016	-0.009	-0.056	0.056	0.020	-0.055	-0.079	-0.033	-0.079
IV2	-0.017	-0.012	-0.032	-0.019	0.027	0.015	-0.020	-0.040	0.007	-0.004	0.341	0.022	0.003	-0.007
IV3	-0.016	0.018	-0.040	0.001	-0.014	0.012	-0.011	0.045	0.001	-0.017	0.022	0.015	0.008	0.013
IV4	-0.050	-0.019	0.001	0.073	-0.013	0.016	0.025	0.047	-0.046	0.034	0.407	-0.001	0.005	0.014
IV5	-0.008	-0.010	0.054	-0.023	-0.006	-0.018	0.007	-0.042	-0.004	-0.008	-0.005	-0.034	-0.009	-0.024
IV6	0.014	0.014	-0.015	0.010	-0.025	0.016	0.023	-0.004	0.031	-0.028	-0.055	0.029	-0.005	0.013
IV7	0.008	-0.003	-0.034	0.016	-0.029	0.012	-0.040	-0.026	-0.004	0.017	-0.054	0.007	0.015	0.009
IV8	-0.007	0.005	0.012	-0.020	-0.008	-0.021	-0.022	-0.032	-0.016	-0.011	0.017	0.013	-0.008	-0.034
IV9	0.033	-0.002	-0.018	0.024	-0.023	-0.005	0.005	-0.021	-0.007	-0.004	-0.063	0.005	0.010	0.003
IV10	-0.102	0.021	0.148	-0.040	0.003	-0.011	0.051	0.238	-0.059	0.105	0.062	-0.060	-0.002	0.015
IV11	-0.010	-0.041	-0.061	-0.011	-0.027	0.026	-0.001	-0.046	0.059	-0.034	0.451	-0.016	0.012	0.009
IV12	0.014	-0.016	-0.011	-0.007	0.253	-0.034	0.000	0.002	-0.040	-0.005	-0.092	-0.026	-0.031	-0.014
IV13	0.338	0.007	-0.010	0.002	-0.035	-0.093	-0.007	-0.025	-0.003	-0.026	-0.022	-0.013	-0.023	0.017
IV14	-0.087	-0.014	0.047	-0.030	-0.009	0.414	-0.016	-0.007	0.020	-0.017	0.028	-0.018	-0.048	-0.015
IV15	0.025	0.022	-0.041	0.056	-0.003	-0.094	-0.052	-0.053	-0.008	-0.033	-0.016	-0.015	-0.009	-0.018
IV16	-0.009	0.003	-0.012	0.000	-0.006	-0.021	-0.006	-0.008	0.017	-0.004	0.001	-0.009	0.506	0.001
IV17	0.001	-0.002	0.016	0.008	-0.005	-0.011	-0.031	-0.014	0.009	0.466	-0.012	0.001	-0.011	-0.010
IV18	-0.123	0.295	-0.034	0.032	-0.013	-0.070	-0.005	-0.006	-0.013	-0.058	-0.027	-0.006	-0.041	-0.026
IV19	0.015	-0.005	0.026	0.031	0.019	-0.010	0.003	0.003	-0.010	0.000	0.018	0.004	-0.006	0.494
IV20	0.002	-0.003	-0.019	0.034	-0.009	-0.019	-0.025	-0.042	0.031	-0.008	0.030	0.017	0.009	-0.009
IV21	-0.081	-0.006	0.063	-0.008	-0.023	0.034	-0.013	-0.020	-0.025	0.019	0.022	-0.048	-0.013	-0.002
IV22	0.015	0.003	0.015	-0.028	0.005	-0.045	0.415	0.010	0.032	-0.046	0.004	0.003	-0.011	0.009
IV23	-0.104	-0.305	0.013	-0.035	-0.001	-0.052	0.001	-0.012	-0.003	-0.059	0.035	0.045	-0.045	-0.043
IV24	0.014	-0.010	-0.020	-0.017	-0.012	-0.009	-0.020	0.405	0.034	-0.051	-0.042	-0.016	-0.021	0.011
IV25	-0.052	0.004	0.027	0.007	0.399	0.009	0.012	-0.016	-0.013	-0.005	0.033	-0.012	0.009	0.029
IV26	0.031	-0.013	-0.036	0.019	0.021	0.026	0.040	0.053	0.070	-0.024	-0.029	0.052	0.019	-0.064
IV27	0.340	-0.010	0.010	-0.015	-0.043	-0.056	0.010	-0.019	0.042	-0.033	-0.010	-0.034	-0.024	0.014
IV28	-0.064	-0.002	-0.033	0.002	-0.022	0.431	-0.069	-0.027	0.041	-0.045	0.040	-0.043	-0.016	-0.014
IV29	-0.022	-0.011	0.025	-0.053	0.005	0.025	0.024	-0.015	0.006	-0.015	0.000	0.036	-0.026	-0.040
IV30	0.017	0.005	-0.011	0.100	0.013	0.005	0.008	-0.031	-0.012	-0.035	0.010	-0.019	0.353	-0.036
IV31	-0.024	0.002	-0.021	0.014	-0.008	-0.030	0.004	-0.032	-0.023	0.473	0.011	-0.030	0.004	-0.008
IV32	0.033	0.007	0.028	0.014	-0.001	-0.023	-0.020	0.009	-0.028	0.032	-0.074	0.008	-0.030	0.015
IV33	-0.047	0.003	-0.015	-0.112	-0.013	-0.042	-0.024	0.020	-0.015	0.048	0.021	0.033	0.377	0.032
IV34	-0.122	0.287	0.007	0.039	-0.011	-0.065	-0.011	-0.007	0.000	-0.065	-0.026	0.014	-0.032	-0.050
IV35	0.010	0.008	-0.002	0.003	0.012	-0.021	-0.011	-0.003	-0.028	-0.018	0.004	-0.008	-0.003	0.501
IV36	-0.031	0.009	0.045	-0.018	0.006	-0.043	0.013	0.004	-0.001	0.016	0.013	0.003	-0.025	0.006
IV37	0.054	0.014	-0.053	-0.008	0.006	0.016	-0.003	0.022	0.004	0.075	-0.007	0.070	-0.003	-0.017
IV38	-0.030	0.086	-0.073	0.083	0.039	-0.058	-0.049	-0.036	-0.118	-0.001	0.040	0.113	-0.013	-0.006
IV39	-0.036	0.004	0.070	-0.045	-0.006	-0.012	0.325	-0.004	-0.017	-0.019	-0.005	-0.032	-0.010	0.014
IV40	-0.111	-0.294	-0.004	-0.013	-0.007	-0.061	-0.019	-0.001	-0.014	-0.063	0.025	0.015	-0.030	-0.036
IV41	0.007	0.003	-0.043	-0.068	-0.017	0.009	0.011	0.455	0.085	-0.049	-0.027	0.017	0.000	-0.017
IV42	-0.052	0.004	0.027	0.007	0.399	0.009	0.012	-0.016	-0.013	-0.005	0.033	-0.012	0.009	0.029
IV43	0.038	0.028	-0.082	0.087	0.004	0.042	0.047	0.011	0.043	-0.023	-0.011	0.050	0.033	-0.020
IV44	0.022	0.013	0.024	-0.051	0.015	0.019	-0.014	0.034	0.022	0.002	0.001	-0.059	-0.061	0.014
IV45	-0.066	-0.068	-0.062	-0.003	-0.019	-0.002	-0.046	-0.046	-0.055	0.007	0.024	-0.038	0.012	0.044
IV46	0.033	0.023	-0.023	0.059	0.023	0.022	-0.040	0.011	0.018	-0.010	0.000	-0.394	0.014	-0.022
IV47	-0.018	-0.009	-0.020	-0.005	-0.016	-0.023	-0.032	-0.013	-0.038	-0.013	-0.008	0.466	0.000	0.025
IV48	0.000	0.026	-0.009	-0.046	-0.016	0.045	-0.011	0.019	0.014	0.024	-0.002	-0.024	0.006	-0.007
IV49	0.003	-0.005	-0.008	0.003	0.011	-0.026	0.359	-0.006	0.016	0.036	0.007	0.016	-0.002	-0.022
IV50	-0.029	-0.036	0.075	-0.062	-0.006	-0.022	-0.007	-0.009	0.015	0.013	0.016	-0.062	-0.028	0.011
IV51	-0.110	-0.011	-0.008	0.041	-0.043	-0.164	-0.046	-0.035	0.045	0.013	0.021	0.012	-0.049	-0.006
IV52	-0.008	-0.020	-0.028	-0.067	0.037	-0.118	0.010	0.044	-0.148	-0.070	0.000	-0.040	-0.040	-0.025
IV53	-0.033	0.020	0.018	-0.013	0.037	-0.031	-0.014	0.027	0.006	-0.012	0.019	-0.044	0.005	-0.015
IV54	-0.003	0.015	-0.030	0.055	-0.062	0.035	0.018	-0.048	0.040	-0.021	0.010	-0.048	0.010	0.007
IV55	0.008	-0.037	0.041	0.166	0.035	0.056	0.058	0.002	0.080	0.084	-0.157	0.020	-0.029	0.035
IV56	0.026	-0.045	0.106	0.104	0.045	-0.051	0.000	0.012	-0.088	0.002	0.036	0.139	0.018	-0.122
IV57	0.069	0.002	0.001	0.078	0.012	-0.015	0.013	0.007	0.090	-0.064	0.061	0.292	-0.016	-0.075
IV58	0.048	0.004	-0.041	-0.023	-0.008	0.026	0.009	0.043	0.501	0.033	0.001	-0.002	0.000	-0.019
IV59	-0.068	-0.001	0.023	-0.067	-0.020	-0.016	0.011	-0.014	-0.055	-0.081	0.028	-0.018	0.016	0.067
IV60	0.026	-0.008	-0.003	-0.003	0.006	0.021	0.037	0.013	-0.018	-0.019	-0.013	0.005	0.051	-0.066
IV61	-0.095	-0.001	0.067	-0.011	-0.002	-0.012	-0.038	-0.022	-0.014	-0.004	0.083	-0.054	-0.008	-0.006
IV62	0.009	0.000	0.012	0.068	0.018	-0.019	-0.020	-0.032	-0.435	0.028	-0.032	0.023	-0.026	0.000
IV63	0.002	0.051	-0.031	0.414	0.012	-0.006	-0.070	-0.011	-0.039	0.014	0.014	0.024	-0.002	0.003
IV64	-0.036	0.029	0.049	0.388	-0.002	-0.008	0.041	-0.087	-0.056	0.019	0.035	-0.037	0.005	0.025
IV65	0.006	-0.017	-0.022	-0.013	0.009	0.005	-0.025	0.008	-0.018	0.041	0.043	0.020	-0.032	-0.015
IV66	-0.068	-0.011	0.171	0.197	0.003	-0.043	0.025	-0.006	-0.011	-0.028	0.020	-0.094	0.010	0.013
IV67	0.006	-0.014	0.296	-0.048	-0.017	0.001	0.009	-0.018	0.163	-0.077	0.003	-0.043	-0.016	0.019
IV68	0.035	0.034	-0.402	0.009	0.000	0.007	-0.037	0.005	0.060	0.000	0.044	0.032	0.038	-0.017
IV69	0.008	-0.031	-0.319	-0.028	-0.021	-0.025	0.025	-0.011	0.054	-0.041	0.034	0.006	-0.021	-0.016
IV70	0.119	0.008	-0.096	-0.030	0.071	-0.080	-0.096	-0.031	0.018	0.018	-0.007	0.116	-0.036	-0.015
IV71	0.011	0.035	0.009	-0.076	0.043	0.094	0.054	-0.087	0.015	-0.008	-0.012	-0.020	0.007	-0.025
IV72	0.066	0.006	0.024	0.049	0.051	0.032	-0.052	0.093	0.061	-0.008	-0.111	0.086	0.026	-0.039



	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
IV1	-0.071	0.014	0.096	-0.024	0.025	0.050	0.078	0.026	-0.072	-0.125	0.094	0.281	-0.101	0.222	0.079
IV2	-0.034	-0.023	0.011	-0.014	0.000	-0.006	0.053	0.015	0.023	-0.035	0.058	-0.044	-0.040	0.262	0.057
IV3	0.020	-0.018	0.063	0.010	0.028	0.007	-0.051	0.039	0.036	0.020	0.021	-0.048	-0.003	0.633	-0.038
IV4	0.028	0.001	0.048	0.015	0.021	0.015	0.002	-0.027	-0.006	0.021	-0.021	0.011	-0.003	-0.076	0.090
IV5	-0.050	-0.005	-0.017	-0.027	0.005	0.036	0.003	-0.017	-0.014	-0.041	0.014	-0.039	0.579	-0.002	-0.021
IV6	0.035	-0.019	-0.002	0.027	-0.417	0.019	0.005	-0.035	-0.023	0.008	0.081	0.152	-0.156	-0.025	-0.185
IV7	0.020	0.045	-0.014	-0.011	0.541	-0.021	-0.016	0.050	-0.026	0.060	0.007	0.153	-0.079	0.007	-0.138
IV8	-0.086	0.034	-0.017	0.007	-0.063	-0.011	0.015	0.060	-0.052	-0.021	0.019	-0.544	0.031	0.082	-0.025
IV9	0.016	-0.042	0.001	0.024	-0.040	-0.031	0.006	0.001	0.009	-0.028	-0.061	0.033	-0.026	-0.016	0.676
IV10	-0.026	0.035	0.039	-0.167	0.072	0.032	0.051	-0.077	0.053	-0.053	-0.128	0.057	0.036	-0.071	0.001
IV11	0.020	-0.014	0.003	0.044	-0.054	0.019	-0.014	0.028	-0.005	0.029	-0.010	0.008	0.003	-0.048	-0.248
IV12	0.013	-0.066	0.045	0.060	0.033	-0.023	-0.057	-0.049	0.182	-0.026	-0.070	-0.092	0.030	0.084	0.047
IV13	0.001	-0.021	0.007	-0.023	-0.019	-0.031	0.049	-0.057	0.013	0.029	0.023	0.015	0.002	-0.022	0.068
IV14	-0.030	0.021	-0.007	-0.014	0.028	-0.023	-0.005	-0.004	-0.010	0.032	-0.024	-0.025	-0.054	0.031	-0.011
IV15	0.025	0.461	-0.035	0.061	0.003	-0.018	-0.055	-0.021	0.088	-0.020	0.093	-0.038	-0.059	0.035	-0.083
IV16	-0.002	-0.011	-0.038	-0.025	-0.002	-0.007	-0.015	-0.005	0.001	0.020	-0.027	0.024	-0.002	-0.004	0.033
IV17	-0.026	-0.014	-0.026	-0.005	-0.008	-0.006	-0.001	0.044	-0.042	-0.024	0.101	-0.009	-0.010	-0.008	-0.025
IV18	0.035	-0.025	0.039	-0.034	0.010	-0.017	-0.007	-0.020	0.023	-0.025	-0.020	0.002	0.007	0.025	-0.021
IV19	-0.019	-0.036	-0.002	0.009	-0.036	0.008	-0.008	-0.006	-0.019	-0.041	-0.022	-0.004	-0.022	0.022	0.010
IV20	0.031	-0.027	-0.082	0.020	0.005	0.471	-0.033	0.007	-0.022	0.004	0.003	0.024	0.158	-0.088	-0.015
IV21	-0.011	-0.037	-0.012	0.036	0.065	-0.007	0.034	0.515	0.016	-0.003	-0.022	-0.034	-0.011	0.075	-0.012
IV22	-0.010	-0.049	-0.009	-0.037	-0.072	0.003	-0.016	-0.061	-0.004	0.004	0.036	0.002	-0.009	-0.027	-0.019
IV23	-0.016	-0.036	0.014	0.035	0.010	-0.020	-0.011	-0.037	-0.029	-0.024	-0.046	0.012	0.037	-0.025	-0.013
IV24	-0.007	-0.042	-0.027	0.060	-0.061	-0.011	0.004	0.038	-0.007	0.078	0.059	-0.014	-0.092	0.017	0.026
IV25	0.000	0.026	0.001	-0.023	-0.019	0.008	0.026	-0.012	-0.083	0.025	0.032	0.047	-0.016	-0.041	-0.038
IV26	0.024	-0.052	0.168	0.059	0.108	-0.006	0.177	-0.015	0.147	-0.053	0.066	-0.005	0.076	0.023	-0.097
IV27	-0.037	-0.005	-0.025	-0.013	0.033	0.011	-0.096	-0.054	0.052	0.011	0.060	-0.021	-0.029	-0.029	-0.004
IV28	-0.010	-0.129	-0.032	0.038	0.007	-0.047	-0.046	0.045	0.069	-0.008	0.063	0.048	-0.003	-0.045	-0.016
IV29	0.022	0.496	-0.018	-0.022	0.046	-0.045	-0.050	-0.026	-0.110	0.010	-0.007	0.043	0.036	-0.058	0.003
IV30	0.063	-0.124	0.059	0.003	0.102	0.001	-0.048	-0.100	-0.034	-0.029	0.159	-0.146	-0.121	-0.082	-0.020
IV31	-0.026	-0.019	0.023	0.007	0.041	0.017	0.017	-0.014	0.047	0.021	-0.101	0.019	-0.016	0.003	0.013
IV32	0.006	-0.040	-0.105	-0.012	-0.130	-0.032	0.478	-0.024	-0.105	0.000	-0.066	-0.108	0.054	0.090	0.146
IV33	-0.103	0.152	-0.112	-0.044	-0.100	-0.023	0.049	0.106	0.062	0.069	-0.227	0.225	0.170	0.161	-0.007
IV34	0.006	-0.035	0.025	-0.030	-0.019	-0.011	-0.001	-0.006	0.001	-0.030	-0.038	-0.010	0.008	-0.001	-0.011
IV35	-0.019	-0.007	0.016	0.024	-0.012	0.000	0.003	0.007	0.010	-0.045	0.037	0.044	-0.024	-0.012	0.013
IV36	0.023	-0.021	0.027	-0.025	-0.015	0.554	-0.005	-0.032	-0.021	0.038	-0.095	-0.007	-0.100	0.082	-0.019
IV37	0.055	0.044	-0.103	-0.025	-0.047	-0.088	-0.048	0.005	-0.135	-0.066	0.498	-0.041	0.035	0.036	-0.131
IV38	0.125	-0.013	0.400	-0.064	-0.060	-0.166	-0.044	0.012	-0.124	0.133	-0.134	0.142	0.095	0.024	0.008
IV39	-0.024	-0.056	-0.036	-0.046	0.008	0.008	-0.011	0.261	0.009	0.010	0.013	-0.037	-0.024	0.045	0.006
IV40	0.008	-0.019	0.007	0.050	0.012	-0.022	-0.005	0.012	0.002	0.003	-0.028	-0.002	0.013	-0.006	0.000
IV41	0.012	-0.043	-0.018	0.009	0.001	-0.027	-0.022	-0.035	0.017	-0.034	0.039	0.026	-0.022	0.107	-0.058
IV42	0.000	0.026	0.001	-0.023	-0.019	0.008	0.026	-0.012	-0.083	0.025	0.032	0.047	-0.016	-0.041	-0.038
IV43	0.042	-0.013	0.124	0.063	0.058	-0.024	0.130	-0.011	0.110	-0.056	0.088	-0.042	0.060	-0.005	-0.089
IV44	-0.037	0.022	0.010	0.424	-0.011	0.082	0.011	-0.042	-0.058	0.026	-0.027	0.041	-0.002	-0.006	0.030
IV45	-0.004	0.025	0.055	0.519	-0.041	-0.060	-0.015	0.101	-0.009	0.044	0.034	-0.047	-0.055	-0.027	0.019
IV46	0.063	-0.019	-0.161	0.041	0.022	-0.042	0.028	0.028	-0.133	0.003	0.026	0.009	0.050	-0.034	-0.024
IV47	-0.036	0.019	-0.101	-0.045	-0.023	0.026	0.035	0.026	-0.110	0.042	0.062	-0.031	-0.021	-0.013	0.000
IV48	0.054	-0.010	-0.010	-0.054	0.001	-0.040	-0.088	0.010	0.553	-0.028	-0.086	0.051	0.010	0.026	-0.024
IV49	0.033	0.068	-0.021	-0.017	0.004	-0.018	-0.049	-0.158	-0.039	0.021	-0.052	0.048	0.028	-0.021	0.038
IV50	-0.112	-0.013	0.498	0.065	0.003	0.065	-0.031	-0.043	0.021	-0.064	-0.063	-0.022	-0.066	0.080	0.019
IV51	0.032	-0.110	0.029	0.006	0.055	-0.034	-0.077	-0.007	0.042	-0.054	0.034	-0.007	-0.034	-0.075	-0.037
IV52	0.275	0.024	0.023	0.173	0.023	0.067	-0.016	0.013	0.053	0.054	0.187	-0.068	0.018	0.093	0.134
IV53	0.450	0.039	-0.044	-0.068	0.020	0.007	0.051	-0.033	0.002	-0.043	0.004	0.033	-0.006	-0.016	-0.097
IV54	0.397	-0.017	0.019	-0.024	-0.019	0.047	0.005	0.010	0.031	-0.001	-0.006	0.085	-0.093	-0.039	0.063
IV55	0.159	-0.063	-0.146	-0.070	0.051	-0.035	-0.023	-0.210	-0.003	0.130	-0.140	-0.159	0.188	0.155	0.004
IV56	-0.025	-0.121	-0.104	0.240	0.058	-0.003	-0.058	-0.121	0.044	-0.138	0.040	0.067	0.017	0.112	-0.030
IV57	-0.040	-0.016	-0.076	0.125	-0.007	-0.089	-0.074	0.009	-0.069	-0.096	-0.143	0.207	0.054	0.024	-0.046
IV58	0.031	0.002	-0.004	-0.021	-0.046	0.007	-0.063	0.026	-0.061	-0.125	-0.097	-0.028	-0.031	0.005	-0.048
IV59	-0.107	0.051	-0.024	0.025	-0.026	-0.024	0.022	-0.055	0.215	0.032	0.276	0.183	0.212	0.034	0.117
IV60	-0.069	0.005	-0.050	-0.015	0.176	0.118	0.010	-0.081	0.031	0.532	-0.076	-0.009	-0.197	0.079	-0.023
IV61	0.008	-0.019	0.018	-0.049	0.051	0.003	0.512	0.040	-0.055	0.017	-0.008	0.115	-0.066	-0.133	-0.077
IV62	0.061	-0.032	0.033	0.019	-0.011	-0.033	-0.065	0.030	-0.079	-0.086	-0.057	-0.112	-0.025	-0.025	-0.005
IV63	0.038	-0.022	0.025	-0.018	0.012	-0.040	-0.037	-0.076	-0.099	-0.008	-0.049	0.017	-0.021	0.000	0.035
IV64	0.007	-0.027	-0.065	-0.017	0.028	0.024	0.006	0.018	-0.022	-0.011	-0.014	-0.019	-0.032	-0.007	-0.005
IV65	0.055	-0.013	0.050	0.074	-0.144	-0.090	-0.021	0.093	-0.063	0.461	0.003	-0.012	0.174	-0.059	-0.033
IV66	-0.141	0.033	-0.017	0.012	0.018	0.088	0.111	-0.165	0.056	0.095	0.139	-0.002	-0.231	0.031	0.120
IV67	-0.034	-0.027	0.096	-0.068	0.022	-0.014	0.013	0.120	0.000	0.076	0.041	0.069	0.054	-0.151	0.023
IV68	0.032	-0.026	0.009	0.012	0.017	-0.037	-0.080	-0.019	0.026	0.012	0.000	0.034	-0.002	0.011	-0.039
IV69	-0.014	-0.016	-0.007	0.053	0.021	-0.001	-0.008	-0.014	0.004	0.035	0.074	0.029	-0.048	-0.017	0.051
IV70	-0.035	0.028	-0.131	-0.049	-0.118	0.014	-0.004	0.279	0.292	0.088	-0.108	-0.091	-0.109	-0.127	0.109
IV71	0.064	-0.168	-0.011	-0.004	0.061	-0.060	-0.051	-0.165	0.024	0.087	0.084	-0.048	-0.092	-0.030	0.042
IV72	0.062	-0.010	0.046	-0.071	0.074	0.066	-0.175	0.192	-0.128	-0.017	0.165	0.042	0.013	-0.067	0.191

## APPENDIX 16 – RIDESHARING MODEL LOGISTIC REGRESSION

### Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Model	104.796	29	0.000

### Hosmer and Lemeshow Test

$\chi^2$	df	Sig.
9.664	8	0.289

### Explained Variation

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
215.298 <sup>a</sup>	0.326	0.465

### Category Prediction

		Predicted		Percentage Correct
		Low-Cost Ridesharing .00	1.00	
Low-Cost Ridesharing	.00	177	12	93.7
	1.00	34	43	55.8
Overall Percentage				82.7

### Logistic Regression

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Factor 1	0.315	0.170	3.432	1	0.064	1.370	0.982	1.913
Factor 2	-0.187	0.185	1.015	1	0.314	0.830	0.577	1.193
Factor 3	-0.016	0.199	0.006	1	0.937	0.984	0.667	1.453
Factor 4	0.632	0.183	11.925	1	<b>0.001</b>	<b>1.881</b>	1.314	2.693
Factor 5	-1.159	0.884	1.719	1	0.190	0.314	0.056	1.774
Factor 6	0.542	0.153	12.538	1	<b>0.000</b>	<b>1.720</b>	1.274	2.323
Factor 7	0.568	0.656	0.748	1	0.387	1.764	0.487	6.386
Factor 8	0.476	0.361	1.738	1	0.187	1.609	0.793	3.263
Factor 9	-0.098	0.180	0.293	1	0.589	0.907	0.637	1.292
Factor 10	0.215	0.149	2.072	1	0.150	1.240	0.925	1.661
Factor 11	-0.025	0.168	0.021	1	0.883	0.976	0.701	1.357

Factor 12	0.288	0.182	2.498	1	0.114	1.334	0.933	1.906
Factor 13	0.488	0.243	4.020	1	<b>0.045</b>	<b>1.629</b>	1.011	2.624
Factor 14	1.037	0.732	2.008	1	0.156	2.820	0.672	11.828
Factor 15	0.483	0.234	4.268	1	<b>0.039</b>	<b>1.620</b>	1.025	2.561
Factor 16	0.328	0.164	4.028	1	<b>0.045</b>	<b>1.389</b>	1.008	1.914
Factor 17	0.529	0.246	4.621	1	<b>0.032</b>	<b>1.697</b>	1.048	2.749
Factor 18	0.218	0.184	1.403	1	0.236	1.244	0.867	1.786
Factor 19	-0.058	0.197	0.087	1	0.768	0.944	0.641	1.389
Factor 20	0.156	0.158	0.976	1	0.323	1.169	0.858	1.594
Factor 21	0.365	0.199	3.364	1	0.067	1.441	0.975	2.130
Factor 22	0.520	0.368	1.992	1	0.158	1.682	0.817	3.460
Factor 23	0.156	0.167	0.873	1	0.350	1.169	0.842	1.623
Factor 24	-0.248	0.245	1.029	1	0.310	0.780	0.483	1.261
Factor 25	-0.827	0.355	5.444	1	<b>0.020</b>	<b>0.437</b>	0.218	0.876
Factor 26	-0.206	0.204	1.022	1	0.312	0.814	0.546	1.213
Factor 27	0.192	0.201	0.912	1	0.339	1.211	0.817	1.796
Factor 28	-0.088	0.193	0.209	1	0.648	0.916	0.627	1.337
Factor 29	0.218	0.168	1.681	1	0.195	1.243	0.895	1.728
Constant	-1.236	0.233	28.022	1	0.000	0.291		

## APPENDIX 17 – GROCERY DELIVERY MODEL LOGISTIC REGRESSION

### Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Model	269.293 <sup>a</sup>	0.304	0.407

### Hosmer and Lemeshow Test

$\chi^2$	df	Sig.
9.048	8	0.338

### Explained Variation

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
9.048	8	0.338

### Category Prediction

		Predicted		Percentage Correct
		Low-Cost Delivery .00	1.00	
Low-Cost Delivery	.00	120	27	81.6
	1.00	39	80	67.2
Overall Percentage				75.2

### Logistic Regression

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Factor 1	-0.203	0.156	1.706	1	0.191	0.816	0.602	1.107
Factor 2	-0.226	0.148	2.341	1	0.126	0.798	0.598	1.066
Factor 3	0.196	0.162	1.471	1	0.225	1.217	0.886	1.672
Factor 4	0.456	0.167	7.508	1	<b>0.006</b>	1.578	1.139	2.187
Factor 5	-0.246	0.515	0.228	1	0.633	0.782	0.285	2.147
Factor 6	0.280	0.149	3.531	1	0.060	1.323	0.988	1.772
Factor 7	-0.020	0.139	0.020	1	0.887	0.980	0.746	1.288
Factor 8	0.841	0.516	2.659	1	0.103	2.319	0.844	6.373

Factor 9	0.135	0.156	0.744	1	0.388	1.144	0.842	1.554
Factor 10	0.273	0.170	2.563	1	0.109	1.313	0.941	1.834
Factor 11	-0.389	0.162	5.768	1	<b>0.016</b>	0.678	0.493	0.931
Factor 12	0.197	0.158	1.543	1	0.214	1.217	0.893	1.660
Factor 13	0.027	0.171	0.025	1	0.874	1.027	0.735	1.436
Factor 14	2.246	0.860	6.828	1	<b>0.009</b>	9.453	1.753	50.967
Factor 15	0.808	0.197	16.797	1	<b>0.000</b>	2.243	1.524	3.301
Factor 16	-0.500	0.236	4.504	1	<b>0.034</b>	0.607	0.382	0.962
Factor 17	0.078	0.207	0.141	1	0.707	1.081	0.721	1.620
Factor 18	0.259	0.159	2.658	1	0.103	1.296	0.949	1.770
Factor 19	-0.094	0.164	0.330	1	0.566	0.910	0.660	1.255
Factor 20	-0.232	0.210	1.215	1	0.270	0.793	0.525	1.198
Factor 21	-0.362	0.228	2.522	1	0.112	0.696	0.445	1.089
Factor 22	-0.081	0.143	0.317	1	0.573	0.922	0.696	1.222
Factor 23	-0.045	0.151	0.088	1	0.767	0.956	0.711	1.286
Factor 24	0.504	0.208	5.902	1	<b>0.015</b>	1.656	1.102	2.488
Factor 25	-0.380	0.208	3.319	1	0.068	0.684	0.455	1.029
Factor 26	-0.471	0.167	7.908	1	<b>0.005</b>	0.624	0.450	0.867
Factor 27	-0.190	0.189	1.013	1	0.314	0.827	0.571	1.197
Factor 28	0.046	0.159	0.084	1	0.771	1.047	0.767	1.429
Factor 29	-0.211	0.160	1.745	1	0.187	0.810	0.592	1.108
Constant	-0.094	0.179	0.276	1	0.600	0.910		

## APPENDIX 18 – VEGGIE BOX MODEL LOGISTIC REGRESSION

### Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Model	85.604	29	0.000

### Hosmer and Lemeshow Test

Chi-square	df	Sig.
5.951	8	0.653

### Explained Variation

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
143.058 <sup>a</sup>	0.275	0.477

### Category Prediction

		Predicted		Percentage Correct
		Veggie box .00	1.00	
Veggie box	.00	23	18	56.1
	1.00	10	215	95.6
Overall Percentage				89.5



## Logistic Regression

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Factor 1	0.766	0.338	5.121	1	<b>0.024</b>	2.151	1.108	4.176
Factor 2	0.542	0.234	5.371	1	<b>0.020</b>	1.720	1.087	2.721
Factor 3	0.792	0.199	15.854	1	<b>0.000</b>	2.207	1.495	3.259
Factor 4	0.162	0.231	0.492	1	0.483	1.176	0.748	1.850
Factor 5	-0.061	0.167	0.133	1	0.715	0.941	0.678	1.305
Factor 6	-0.046	0.228	0.040	1	0.841	0.955	0.611	1.492
Factor 7	-0.161	0.146	1.225	1	0.268	0.851	0.639	1.133
Factor 8	0.263	0.444	0.352	1	0.553	1.301	0.545	3.105
Factor 9	0.265	0.240	1.216	1	0.270	1.303	0.814	2.087
Factor 10	-0.329	0.176	3.476	1	0.062	0.720	0.509	1.017
Factor 11	0.686	0.379	3.267	1	0.071	1.985	0.944	4.176
Factor 12	0.743	0.254	8.545	1	<b>0.003</b>	2.103	1.278	3.461
Factor 13	0.011	0.300	0.001	1	0.970	1.011	0.562	1.820
Factor 14	-0.269	0.171	2.489	1	0.115	0.764	0.547	1.067
Factor 15	0.251	0.227	1.226	1	0.268	1.285	0.824	2.005
Factor 16	-0.243	0.167	2.116	1	0.146	0.784	0.565	1.088
Factor 17	-0.374	0.287	1.699	1	0.192	0.688	0.392	1.207
Factor 18	0.427	0.205	4.368	1	<b>0.037</b>	1.533	1.027	2.290
Factor 19	0.014	0.257	0.003	1	0.957	1.014	0.613	1.678
Factor 20	-0.380	0.155	5.982	1	<b>0.014</b>	0.684	0.505	0.927
Factor 21	-0.119	0.253	0.221	1	0.639	0.888	0.541	1.457
Factor 22	-0.242	0.168	2.063	1	0.151	0.785	0.565	1.092
Factor 23	-0.302	0.216	1.949	1	0.163	0.740	0.484	1.130
Factor 24	0.194	0.312	0.387	1	0.534	1.214	0.659	2.238
Factor 25	-0.344	0.211	2.662	1	0.103	0.709	0.469	1.072
Factor 26	0.453	0.244	3.434	1	0.064	1.573	0.974	2.538
Factor 27	0.301	0.249	1.470	1	0.225	1.352	0.830	2.200
Factor 28	0.341	0.235	2.099	1	0.147	1.406	0.887	2.229
Factor 29	-0.181	0.219	0.678	1	0.410	0.835	0.543	1.283
Constant	2.845	0.365	60.916	1	<b>0.000</b>	17.207		