Consumer Preferences and Associated Price Premiums for Agricultural Traits in Maine Markets

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CONSUMER PREFERENCES AND ASSOCIATED PRICE PREMIUMS
FOR AGRICULTURAL TRAITS IN MAINE MARKETS

By

Lauren Miller

B.S. Economics and B.S. Environmental System Science, University of Wyoming 2019

A THESIS

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In this thesis, I investigate the roles of both consumers and producers in the emergence of traited (i.e. local and organic) goods markets in Maine. I discuss welfare changes after differentiation of the market as well as the impact of changing consumer preferences on market outcomes.

The first chapter motivates the emergence of traited goods markets—as consumers try to satisfy their preferences and producers seek to increase incomes.

The second chapter explores the market for traited goods in Maine, focusing on the evolution of consumer preferences. A market differentiation framework is used to consider factors that impact total welfare changes in differentiated agricultural markets. The fraction of consumers who transition to the new market, the number of consumers in the
market, and the price of the differentiated good are a few of the factors found to influence the magnitude and sign of welfare changes after differentiation. The chapter ends by discussing the costs of production and the decision facing producers when the costs of producing a trait involve substantive production changes.

The third chapter of this thesis uses an agent-based model (ABM) to simulate the evolution of consumer preferences through learning. The ABM models a market of consumers who undergo two types of learning (experiential and social) and adjust their preferences according to what they have learned. Consumers make a purchase decision each week based off of their current preferences for a total of 5 years. Results from the simulations show that learning has significant impact on preferences and market outcome. Social learning facilitates the spread of information shocks and general trends. Experiential learning (when set to occur only after an experience with local food), resulted in lower average preferences market-wide because it can result in consumers exiting the local food market but does not provide a pathway for new consumers to enter. The long-term impact of shocks to the market is found to be related to the level of learning present within the system. With more active learning, the effects of the shocks die out more quickly.
DEDICATION

This is dedicated to my family who have steadfastly supported me and provided me with endless patience and support as I’ve buoyed between fields of study. Thank you for your hard work that has allowed me to pursue my own dreams. Most especially, this thesis is dedicated to the memory of my grandmother and other women like her, who studied economics when it seemed bizarre for any woman to do so. Thank you for blazing the trail so that I may have the opportunities that you were not allowed.
ACKNOWLEDGEMENTS

Thank you to my committee for your support, guidance, and for allowing me to pursue research that I am passionate about. Also, thank you to my cohort for your support, friendship, and for patiently listening to all of my rambling over the last two years. Lastly, a very special thanks to my advisor. This thesis would still be just an idea in my head if it wasn’t for his unwavering support, guidance, and patience over the last two years.
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CHAPTER 1

MOTIVATION FOR DIFFERENTIATING MARKETS

The modern food system is an intricate network that plays a central role in sustaining human life. At the very core of the food system are agricultural producers. These producers create the basic goods that make up most of human food consumption, including both the consumption of unprocessed goods and goods that have been processed into value-added products. At the other end of the food system are consumers. The two ends of the food system are intrinsically connected: consumers have access to the products that agricultural producers chooses to cultivate, and the preferences of consumers in the market influence what producers choose to grow.

In the state of Maine, between the two most recent agricultural censuses (2012 and 2017), average net cash farm income decreased by 16%, dipping to $16,958 in 2017. This drop in income is likely to push farmers to look for ways to either increase their revenues or decrease their costs. One method for increasing revenue is to more effectively match production to consumer tastes. This can be done by producers identifying process-created traited goods (such as local or organic food) for which consumer demand is rising and matching production to these trends. Producers must also use their judgement to determine the stability of the niche. If demand for the good rapidly falls, producers may be left worse off than before as they may be saddled with surplus goods.

In this thesis, I examine the effects of establishing differentiated Maine markets for traited agricultural goods on producer and consumer welfare in Maine. In particular, I study the changes to producer and consumer surplus—a measure of social welfare—after
the emergence of a differentiated market for "local" agricultural goods. I also consider the impacts of costs on producer welfare and the factors that impact the sign and magnitude of welfare changes. Our emerging understanding of preferences, however, suggests that consumer preferences may not be static. To investigate the effects of changing preference on market outcome, I create an agent-based model (ABM) to simulate information transmission and preference evolution amongst consumers in a food market.

The topics considered in thesis grew out of the observation that both consumers and producers have shown an increased interest in traited agricultural goods over the past few decades. There are certain qualities and certifications of differentiated agricultural products toward which farmers have been turning towards in recent years. Two particular traits that have risen in popularity for both producers and consumers are foods produced locally and foods produced on organically certified operations. Organic foods sales in the U.S. have more than tripled between 2007 and 2015. Similarly, the value of U.S. direct from farm sales to consumers went from $1.7 billion in 2007 to 2.8 billion in 2015 (USDA, 2019).

Maine, specifically, has observed rising sales of local and organic food. According to the latest Agricultural Census (collected before the pandemic), 27% of Maine farms sell products directly to consumers and 7% of Maine farms are certified organic (USDA, 2019). While 7% may seem an inconsequential share, it is significantly higher than the national average which is under 1%. Maine has seen one of the highest growth rates in certified organic farms in the country; between the 2012 and 2017 agricultural censuses, Maine’s sales of organically certified products grew nearly 65% (USDA, 2014). The state has also seen a high rate of increase for local sales, between the 2012 and 2017 Agricultural Census direct to consumer sales increased from around $25 million to around $38 million. While
these figures have risen, the number of farms and the value of goods sold have been decreasing over recent years (USDA, 2019). This seems to indicate that while some farmers are leaving the market, those who are staying are increasing their production of differentiated goods, at least of organic and local goods.

Though local and organic food are two of the fastest growing and most prominent traits, there are other traits including non-GMO, cage-free, Certified Humane, free range, rBST-free, Fair Trade, etc. that are used to differentiate goods. These traits are all characteristics within the process of producing the good and are therefore unidentifiable to consumers without explicit marketing.

The motivation for producers to shift production to traited goods stems from the fact that many traited goods can be sold with a price premium, meaning that producers can sell one unit of a traited good for more than one unit of a conventional good \(^1\). As many traits are "process-created" attributes and, thus, not directly observable to consumers at the time of purchase, producers must take direct action if they hope to take advantage of a consumer’s desire to obtain traited goods. In order to capture consumers’ willingness to pay a premium for a trait, producers must make it known to them. This can be done by obtaining third-party certifications or through other marketing practices (Goodhue, 2011).

The high costs of agricultural production and the risk of changing preferences leaves producers facing a fairly risky decision. To avoid losses, it is important for producers to not only know what trends are popular among consumers but how these trends may change in the coming years.

\(^1\) I will be addressing undifferentiated goods as "conventional" goods and differentiated goods as "traited" goods.
The demand for local food, in particular, has been steadily rising in demand within the state of Maine as well as rising in response to the COVID-19 pandemic. While trends for local and organic foods have been on a steady rise for several years, the COVID-19 pandemic has placed a renewed focus on agricultural markets. Many consumers have become more conscious of food sourcing as supply chain inadequacies coupled with hoarding behaviors left grocery stores empty in early March, turning attention to the agricultural production (Luckstead et al., 2020).

Early studies from 2020 show a trend of higher demand for local food amidst the COVID-19 pandemic. Suspected motivation for increased local food demand includes a desire to avoid conventional shopping centers, a desire to stimulate the local economy, and perception of a lesser risk of virus exposure from local food (Hobbs, 2020). It is important to note that the perception of increased safety with local supply chains is an often-incorrect perception, as studies have shown that local supply may actually be at a higher risk of contamination than grocery store supply due to the number of intermediaries dealing with the product and looser regulations (Aiyar and Pingali, 2020).

Perception of traited goods also has a larger context outside of the COVID-19 pandemic. One of the issues with marketing foods as “local” is that it is an unregulated label. This means that to some consumers, “local” goods include those supplied in grocery stores which come from neighboring states whereas to other consumers it may mean only direct from farm sales through avenues such as on farm sales, farmers markets, or programs such as CSAs. Ambiguous perception is not exclusive to local foods, other traits such as organic may have misconceptions about inputs in the production process as well as physical attributes of the good. This ambiguity may be to the detriment or benefit of the
producer. After all, the purpose of differentiated marketing is to identify consumer segments who are willing to pay extra for these food traits. If a trait is unregulated or associated with misinformation, that may mean that consumer perception is likely to change over time. As consumers are exposed to new information, beliefs founded on misinformation may begin to shift, potentially resulting in decreased demand for traited goods. The diverse perception of traits is one motivator for the creation of the agent based model which looks at how preferences change over time. If preferences changes thus changing demand, production may exceed demand, causing producers to lose profits because of the slow and prefixed nature of agricultural production. For this reason, knowing how these preferences for specific traits are formed and communicated, and how they change in response to shocks (such as the COVID-19 pandemic).

This thesis proceeds as follows: in the next chapter, I study the welfare implications of the emergence of traited goods markets, particularly local markets and the choice facing producers as they debate whether to join the new market. I find that the sign and magnitude of welfare changes after differentiation depend on a variety of factors, including the number of consumers in the market, the portion of consumers that exit the market for the differentiated good, and the price of the differentiated good. In my second chapter, I build an agent-based model (ABM) to examine consumer preference evolution through learning. I also examine the effect of shocks, to model events such as that of COVID-19, and find that the long-term impacts of shocks are largely mitigated by the prevalence of learning in the system.
CHAPTER 2
WELFARE CHANGES IN DIFFERENTIATED AGRICULTURAL GOODS MARKETS IN MAINE

2.1 Introduction

The importance of process-created traits has a long history in agricultural markets. Iconic examples of goods differentiated by locality include wine produced exclusively in the Champagne region of France and balsamic vinegar of Modena, Italy. While differentiated markets for goods such as these have long existed, the late twentieth and now twenty-first centuries have seen the emergence of new certifications and practices that have differentiated markets that used to be comprised of largely homogeneous goods. Many of these new certifications revolve around social issues such as environmental protection, agricultural worker health, and animal welfare.

While producers may be able to differentiate their goods through simple marketing changes, certain traits may require production changes. In agriculture, implementing a production change is no easy feat. Production plans, including the purchasing of inputs, may be decided a year or more in advanced. Crop rotations may be decided years in advanced, and certifications such as organic carry large upfront costs and require several years of planning to implement. Especially for small farms whose families rely solely upon their farm income to survive, the implications of a production shift are important to know prior to the shift being implemented. In this chapter, I will explore how the emergence of differentiated markets affects consumer and producer welfare to better understand under what conditions production of differentiated goods may improve market welfare.
The United States has seen clear trends in both the production and consumption of differentiated agricultural products (such as goods marketed as local and organic). While certain food traits, such as organic, require certification and input changes, selling food as "local" is a change in how food is marketed. The sales of food marketed as local has grown in recent years. The trait "local" can be subjective, as it has no standard definition. Because of this, I will use direct-to-consumer sales as a proxy for the "local" trait. The number of farms utilizing direct-to-customer (DTC) marketing in the United States has grown over the last twenty years (USDA, 2019). Between 1994 and 2016, the number of farmers market directories listed in the United States increased by more than 400% (Low et al., 2015). Maine, specifically, has seen an increase of both DTC sales and organic sales that exceed the national average (USDA, 2019).

In this chapter, I derive the changes in welfare that result from the emergence of a market for traited goods. I focus on local goods because traited local goods typically requires a marketing change and not a significant change of inputs or certification on the part of the farmers, which simplifies the analysis as it implies negligible changes in the supply curve. I examine the current state of local goods markets in the state of Maine, and using a generalized framework, consider how changing market characteristics may impact consumer and producer welfare in Maine. Although I focus on the market for local traited goods, I also explore how this framework could be applied to markets of other traits that require more substantive cost changes such as certified organic goods.

The chapter concludes with a discussion of the effects of the COVID-19 pandemic on traditional grocery shopping habits (Grashuis et al., 2020). Preliminary research has shown that perceived health risk has resulted in an increased preference for local food (Butu
et al., 2020). This could mean that Maine’s DTC value continues to increase. The impacts and longevity of the ongoing COVID-19 pandemic are important to consider when projecting future growth of traited goods markets in Maine.

### 2.2 Traited Good Markets

There are many different traits that can differentiate one agricultural good from another, ranging from the product itself to the process in which the product is made or marketed. Characteristics of the product, also known as inherent characteristics, are verifiable by examining the product. Characteristics may include weight, taste, color, etc. Process-created traits, however, are not verifiable by the buyer at the time of purchase. Process-created traits may include the types of seeds that were grown or the fertilizers that were used during production. In recent years, differentiation has increasingly shifted to earlier stages in the production process. Goods are now often differentiated at the production stage—for example organically produced corn versus conventionally produced corn (Goodhue, 2011).

The process of transitioning production can be costly and slow. For example, transitioning to organic production often takes three years (USDA, 2021). For this reason, growers want to be looking to the future when considering consumer preferences for the trait in question. Coordination between growers and consumers allows for sufficient supply to be available to match demand. In the state of Maine, a lot of coordination is done through grower networks, such as the Maine Organic Gardening and Farming Association (MOFGA), that offers support and guidance to growers. MOFGA specifically helps growers in transitioning to organic and currently supports over 500 organic producers in the state.
Maine also has the Maine Federation of Farmers Markets which assists growers to coordinate with organizers of local markets. Associations such as these create networks for growers to connect with other growers to learn from each other’s successes and challenges.

2.2.1 Local Food Production in Maine

Quantifying current sales of foods marketed as local is difficult due to the lack of regulation of the term. The USDA unofficially defines a "local" good as a good produced within the same state or within a 400 mile radius (Low et al., 2015). The definition is not regulated, however, meaning that anyone can market a good as "local". The ambiguity of the term makes it much more difficult to quantify the current market in the state for goods marketed as local as opposed to the markets of regulated labels like organically certified foods. A survey conducted by the Atlantic Corporation in 2020 shows how Maine consumers view the term "local". Nearly 40% of respondents consider foods local if they were produced in a 25 mile radius. Cumulatively, around two-thirds of the respondents said that for food to be considered local, it needs to be produced within a 50 mile radius or 25 mile radius (see Figure 2.1). For reference, fifty miles is roughly the distance from Bangor, ME, to Bar Harbor, ME.

There are many ways for consumers to acquire local food. Farmers markets are often the outlet most associated with selling local goods. This holds for Maine, as seen in Figure 2.11, which shows that around half of surveyed individuals frequent farmers markets for purchasing local food. Additionally, over 40% of respondents frequent farm stands.

1The survey did not include an "I do not purchase local" option, meaning that the views represented are from consumers who purchase local goods and may not be representative of all Maine consumers.
The count of farms utilizing DTC sales rose between the 2012 and 2017 rounds of the agricultural census (Figure 2.2), particularly among farms averaging DTC sales of $50,000 or more, between the 2012 and 2017 census (see 2.2 left). The count of farms selling any amount of goods DTC rose most significantly in farms with total sales ranging between $500 to $4,999 and fell most significantly in farms with total sales between $5,000 to $9,000 (see 2.2 right).

Figure 2.2. Average DTC Sales on Farms Utilizing DTC Channels (Left) and Count Farms Selling DTC by Total Sales Value (Including Channels Besides DTC) (Right) (USDA, 2019)
While sales value and acreage need not be directly related, the trends observed in Figure 2.2 are similar to those of Figure 2.3. Figure 2.3 shows the changes in the count of farms by acreage. The count of mid-sized farms decreased, while the count of small farms (1 to 10 acres) and large farms (2,000 or more acres) has increased since 1987. While the increase in large farms may seem insignificant on the graph, the count of farms with an acreage above 2,000 acres increased from 49 in 2007 to 70 in 2017. Using the most conservative estimation of all farms in this category having an acreage of 2,000, this is an increase of 42,000 acres of farmland solely from the growth of the number of large farms over a ten year period (USDA, 2019).

![Figure 2.3. Historic Size of Maine Farms. Data: (USDA, 2019) Over the past few decades, the sales value and total costs of agricultural production in Maine steadily increased; however, between the 2012 and 2017 Agricultural Censuses, both of these values decreased. (USDA, 2019). Table 2.1 shows the total costs of all agricultural producers in Maine (in thousands of dollars), the value of all agricultural products]
produced in Maine (in thousands of dollars), as well as these values on a per-acre level and the net profits per acre. The trend of decreasing profits on a statewide level between 2007 and 2017 contrasts the rise in the count of farms selling DTC. The disparity between these two trends may mean that Maine producers are successfully utilizing local marketing in order to increase their personal profits during a period of time when profits are declining on a statewide level.

### Table 2.1. Costs and Sales Value of Maine Agricultural Products (USDA, 2019)

<table>
<thead>
<tr>
<th>Year</th>
<th>Total Acres of Farmland</th>
<th>Total Costs (in thousands)</th>
<th>Average Costs Per Acre</th>
<th>Total Value Agricultural Products (in thousands)</th>
<th>Average Sales Value Per Acre</th>
<th>Net Profits Per Acre</th>
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<td>1,307,613</td>
<td>$586,564</td>
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### 2.2.2 Organic Food Production in Maine

Organic farming in Maine does not have as much historic data available as DTC sales. However, data from the most recent Census of Agriculture shows that there are clear trends in the growth of the number of farms with a sales values over $50,000 as well as a decrease in farms with sales values under $25,000 (Figure 2.5).
Examining the data from the 2017 Census of Agriculture, regarding organics, two visible trends appear. First, the vast majority of sales value from Maine organic producers came from operations that made $50,000 or more. Additionally, the count of organic farms by sales value shows that there are many farms with a sales value under $20,000 and many farms with a sales value over $50,000 but there are not many farms who fall into the mid-range category of farms having a sales value $20,000 to $50,000 (Figure 2.5).

Figure 2.4. Count of Organic Farms by Sales Value. Data: (USDA, 2019)

Figure 2.5. Count of Organic Farms by Sales Value. Data: (USDA, 2019)
While many factors influence producers’ decisions to produce traited goods, principle among them is the belief that, by doing so, they can improve the economic well-being of their operation. The general trends of recent years are not guarantees of future trends, but farmers must make decisions regarding production changes with the information available to them.

In the next section, I discuss how consumer preferences for traited goods translate into a market price premium that can be captured by producers and benefit consumers by providing the goods that they prefer. To simplify this discussion, I begin by narrowing traits to focus specifically on goods marketed locally.

### 2.3 Utility & Willingness-to-Pay

In the previous section, I documented the rise in the marketing of traited goods. Producers were hypothesized to shift into producing these traits to take advantage of higher prices in these markets. This “price premium”—the difference in price obtainable from selling the traited good versus an undifferentiated good—has its roots in consumer preferences.

Consumer preferences refer to how consumers rank a discrete set of alternatives. For example, a consumer may be presented with a set of goods that includes a conventional good and a local good. It is assumed that a consumer is able to rank these goods based off of the satisfaction, or utility, that they gain from consuming the good. Consumers are assumed to choose the good or basket of goods that is the “most preferred” subject to their budgets and the prices of the available goods.
A consumer’s willingness-to-pay (WTP) for a particular trait is the additional amount the consumer would pay to obtain one unit of the traited good rather than one unit of the undifferentiated good.

Data collection methods for willingness-to-pay estimates can be split into revealed and stated preference methodologies. Studies surrounding WTP can be used for tangible goods as well as non-market goods. The estimation of WTP for traited agricultural goods contains both tangible and non-market aspects. Tangible aspects of the good include taste, size, and color, whereas the non-market qualities of the goods are the process-created attributes discussed earlier in the chapter such as reduction in pollution from choosing organic farming over conventional. Data collection for WTP studies of agricultural products can come about from market data, experiments, direct surveys, or indirect surveys (Breidert et al., 2006). The various methodologies for collecting data for WTP estimates can be seen in Figure 2.6.

![Figure 2.6. WTP Methods (Breidert et al., 2006)](image-url)
There are several ways to model WTP estimates once data is collected. The model and estimator used typically depend on how the data was collected. The impact of various attributes and sociodemographic factors on WTP estimates are typically derived using discrete choice estimators such as probit and logit models (Loureiro and Hine, 2002).

One popular way of estimating WTP is through contingent valuation (CV). Within a contingent valuation framework, consumers are asked to directly report an estimate of WTP. This may be done by soliciting a response directly through a bidding process (i.e. "would you pay X amount for this trait?") or by asking consumers to list how much they would be willing to pay for a good. In a CV framework, WTP can be modeled as in Equation 2.1 where WTP is a willingness-to-pay estimate, $X_i$ is a vector of observable attributes impacting WTP estimate, $\beta$ is a corresponding vector of parameter estimates, and $\varepsilon_i$ is a mean zero error term containing the unmeasurable aspects of preference. (Ready et al., 1996).

\[
WTP = X_i \beta + \varepsilon_i \tag{2.1}
\]

Other ways of calculating WTP, such as choice experiments, require the researcher to infer WTP based off of the decision made by the consumer over a set of discrete choices. The researcher can use the traits of the goods, price, and other information to estimate a marginal WTP estimate (as price increases, how does their choice related to the trait increase), through parameter estimates as shown in Equation 2.2:

\[
MWTP_{mean} = \frac{\beta_1}{\beta_2} \tag{2.2}
\]
Where $MWTP_{\text{mean}}$ is the marginal willingness-to-pay at the mean, $\beta_1$ is the parameter estimate of the attribute of interest, and $\beta_2$ is the parameter estimate of the price of the good (Nganje et al., 2011).

There are advantages and disadvantages to each of the various methodologies within both stated and revealed preferences; however stated preferences, most particularly direct surveys, have endured criticism for their hypothetical bias (Loomis, 2011). This stems from the idea that consumers are not always accurate judges of their own future behavior and values. That does not mean that stated preference methods are obsolete, however they are often examined critically. There have been increasing interest in studying stated preference and actual decision making which has led to potential ways to identify and correct this hypothetical bias (Schläpfer and Fischhoff, 2012).

Revealed preferences, particularly through market data, may be preferable because they show data from true purchasing behavior. However, market data can be difficult or costly to acquire and the layout/availability of selection may make certain inferences around WTP difficult to make. Experiments may introduce their own forms of bias, particularly selection (including self-selection) bias. Additionally, revealed preference studies only considers consumers who currently purchase the good in question, which must already be available on the market.

If consumer preferences for the local and non-local good are rational (ie. complete and transitive), they can be represented by a utility function.

To choose between consuming the local (l) and non-local (c, for conventional) goods, the consumer first derives the utility for each good and solves the following utility maximization equation, where they choose a bundle of local (l) goods to consume, subject
to a budget constraint equation, including their wage ($W$), and then choose the quantity to consumed based on the value of that bundle:

$$\max_{q_l} U(\text{local}) \quad s.t. \quad p_l q_l \leq W$$

$$v(\text{local}) = U(q_l^*)$$ (2.4)

A similar equation can be formed to represent conventional good consumption:

$$\max_{q_c} U(\text{conventional}) \quad s.t. \quad p_c q_c \leq W$$

$$v(\text{conventional}) = U(q_c^*)$$ (2.6)

Having done so, the consumer can compare the utility obtainable from each of her two alternatives. This is done by substituting the optimal quantities of the local/non-local good back into the utility function. The result is an indirect utility function that is a function of a variety of factors including attributes of the good, price, income, and available information (this will be discussed more in-depth shortly).

Food choice and food reference literature include a wide array of data collection methods. Although collection methods vary, the foundation for calculating WTP estimates are based upon Random Utility Theory. Random utility theory assumptions are divided into four categories, as illustrated in the Table 1.1. Random Utility Theory informs one of the most commonly used models in consumer choice, the random utility model (RUM).
Random utility models (RUM) are used to quantify how much value (or utility) a consumer gains from consuming a good given their consumer preferences, demographics, and attributes of the products. Random utility models split utility into an observable measure of preference (which is known by both the consumer and researcher) and unobservable elements of preference (which are known by the consumer but not the researcher). The indirect utility that an individual receives will be a function of the price of the good \( p \), a vector of attributes of the good \( Q \), information \( I \), income \( y \), and an error term capturing non-measurable aspects of preference \( \varepsilon \). In this example, the subscript \( l \) signifies the variable is in relation to the local good; the subscript \( c \) indicates non-local good.

In Equation 2.9, \( \varepsilon_i \) captures the random elements of both the local and conventional utility \( \varepsilon_i = \varepsilon_{il} + \varepsilon_{ic} \). These random elements of utility are additively separate than the observable elements of utility.
This property is why the equation can be arranged as in Equation 2.9:

\[ \text{Non-local good : } v_{ic} = v(p_{c}, I_{Qc}, \varepsilon_{ic}, y_{i}) \quad (2.7) \]

\[ \text{Local good : } v_{il} = v(p_{l}, I_{i}, Q_{l}, \varepsilon_{il}, y_{i}) \quad (2.8) \]

\[ v_{il}(Q_{l}, y_{i} - p_{l}) - v_{ic}(Q_{c}, y_{i} - p_{c}) > \varepsilon_{i} \quad (2.9) \]

The individual will choose to consume the local good instead of the non-local good, if Equation 1.3 holds. As long as the difference between the utility they gain from local and the utility they gain from a conventional good is greater than the sum of the random elements of utility of both of these goods, they will choose to consume local. Equation 2.9 can be rewritten to include the market price premium of a given good \((R)\) as in Equation 2.10.

\[ v_{il}(Q_{li}, I_{i}, y_{i} - (p_{c} + R)) + v_{ic}(Q_{c}, I_{i}, y_{i} - p_{c}) > \varepsilon_{i} \quad (2.10) \]

Equation 2.10 demonstrate what conditions must hold for an individual consumer to choose to consume a local good instead of non-local good. If the statement does not hold, an individual will choose to consume a non-local good. If the statement holds, the utility gained from the treated good with the associated price premium is greater than that of the conventional good despite its higher price. In other words, the consumer is willing-to-pay the price premium \((R)\) of the local good.
2.4 Product Differentiation & Market Segmentation

One of the main enticements for production changes is the chance to obtain the price premiums that consumers are often willing to pay for "local" goods. This is done through a simple marketing change. For example, perhaps previously all potatoes were dumped into one bin as a store and marketed simply as potatoes. Now, say the Maine potatoes are separated, labelled as 'local', and sold for $.05 more per pound.

To show the differentiation of local goods in an undifferentiated market, I start by creating a linear model of the market for an undifferentiated good. The demand of an individual consumer (i) can be written:

\[ q_i = A - BP^M \]  \hspace{1cm} (2.11)

Market demand is the summation of the individual (i) demand functions for all consumers (n) the market, assuming they are identical.

\[ Q_{undiff} = \sum_{i=1}^{n} q_i = \sum_{i=1}^{n} a - bP^M = nA - nBP^M \]  \hspace{1cm} (2.12)

This can also be rearranged to form the equation for the inverse demand curve:

\[ P_{undiff} = \frac{A}{B} - \frac{1}{Bn}Q \]  \hspace{1cm} (2.13)

The supply of this undifferentiated market consists of both goods produced by local producers as well as imported supply as shown by \( Q^L \) and \( Q^M - Q^L \) respectively in Figure 1.2. The quantity of goods produced locally is dependent on the total number (k) of individual producers (j) in the market. In Figure 2.7, it is demonstrated that individual
producers are price takers and will produce a quantity that is a function of the exogenous market price. I make the assumption that producers will choose to produce zero goods when the price is zero. The supply function of an individual local producer is given as:

\[ q_j = DP \]  

(2.14)

Summed over all \( k \) producers, this yields:

\[ Q_{\text{undiff}} = \sum_{j=1}^{k} q_j = \sum_{j=1}^{k} DP = kDP \]  

(2.15)

This can be rearranged to form the inverse supply function:

\[ P_{\text{undiff}} = \frac{1}{kD}Q \]  

(2.16)

Figure 2.7. Local Market for Undifferentiated Good
Figure 2.7 shows the demand for undifferentiated goods at the market level (left) and the supply provided by one individual producer (j) in the market (right). Within the demand of the local market, total quantity supplied is the sum of imports from outside of the geographical market area and locally produced goods. In the undifferentiated market, a locally produced market is identical to an imported product.

Using this framework, the consumer and producer surpluses in the undifferentiated market can be calculated. These welfare measures are shown in Equations 2.171-4:

\[
\begin{align*}
1 & \quad \text{Local Producer Surplus} \quad PS = \frac{1}{2}kD(P^M)^2 \\
2 & \quad \text{Consumer Surplus} \quad CS = \sum_{j=1}^{k} PS_j = \frac{1}{2}(A_B - P^M)(nA - nBP^M) \\
3 & \quad \text{Market Quantity Demanded} \quad Q^* = An - BnP^M \\
4 & \quad \text{Price Elasticity of Demand} \quad \epsilon_d = \frac{\partial Q}{\partial P} \frac{P}{Q} = -\frac{BnP^M}{A_n - BnP^M}
\end{align*}
\]

In an undifferentiated market, goods are assumed to be uniform and the market contains both local and non-local producers, although local producers are not utilizing marketing practices to sell their goods as "local" goods. In this market, the demand, supply and market welfare measures can be derived (seen in Equations 2.171-4 and Figure 2.7).
Total welfare is the sum of consumer surplus and producer surplus as shown in Equation 2.18.

\[ TW_{undiff} = CS_{undiff} + PS_{undiff} \]  \hspace{1cm} (2.18)

Equations 2.171-2 can be substituted into Equation 2.18 above to further specify welfare, as in Equation 2.19 below.

\[ TW_{undiff} = \frac{1}{2} \left( (\frac{A}{B} - P^M)(nA - nB^M) + kD(P^M)^2 \right) \]  \hspace{1cm} (2.19)

As the market price of a good changes, we see how each of the three welfare measures change. It can easily be observed from Figure 2.7 that as price increases, consumer surplus decreases and producer surplus increases. Producer surplus will continuing increasing as price increases as long as price does not exceed the choke point where \( P = \frac{A}{Bn} \). At this point, the consumer demand crosses the y-axis, meaning that if the price is above this point the quantity demanded will be zero.

In order to take advantage of consumer preferences and increase viability of farm livelihoods, we can consider facilitating the creation of a traited goods market. Maine has several campaigns promoting Maine made goods. "Maine Made" and "More Maine Meat" both strive to help producers market their goods in such a way as to take advantage of consumer’s willingness to pay for the “local” trait.
2.5 Differentiating the Market

After differentiation, locally produced goods are now marketed as "local" and consumers either consume local or non-local goods. In this case I am making the assumption that individual local supply functions are remaining the same (assuming the most basic marketing change for "local" differentiation). In this case, we are assuming that a portion of the consumers (\(\alpha\)) are moving to the local market and that the remaining consumers (\(1-\alpha\)) are consuming non-local (conventional) goods.

![Diagram of Differentiated Markets for Local and Non-Local Goods]

Figure 2.8. Differentiated Markets for Local and Non-Local Goods

As \(\alpha\) consumers leave the conventional market for the local market, the demand curve for conventional food will shift left and rotate inwards. Since the total number of consumers is decreasing in the conventional market, the slope of the demand curve will
grow steeper. In the differentiated market, the local producers are still price takers but are no longer subject to the exogenous commodity market price. Instead, the price in the local market occurs at the equilibrium of the supply and demand curves.

The consumption in the non-local market will be a summation of the individual demand curves of the consumers in the market and the consumption in the local market will be a summation of the individual demand curves of the consumers in the market. The supply curves of an individual producer in the conventional market has not changed, however the market supply has changed due to consumers exiting the conventional market for the local market. This can be shown as:

$$Q_C = \sum_{i=1}^{(1-\alpha)n} q_i = \sum_{i=1}^{(1-\alpha)n} A - P_c = n(1 - \alpha)(A - P_c) \quad (2.20)$$

This can be rearranged to form the inverse demand equation:

$$P_C = \frac{A - \alpha A}{B - \alpha B} - \frac{1}{nB - \alpha nB}Q_c \quad (2.21)$$

The supply of the local market involves the local price ($P_L$) and local quantity ($Q_L$):

$$P_L = \frac{1}{kD}Q_L \quad (2.22)$$

In the market, an individual consumer has a value that they are willing to pay for the traited good over a conventional good:

$$q_i = A + R_iB + BP_L \quad (2.23)$$

This is noted as $R_i$. Because all consumers are assumed to be identical, $R_i$ is also the exact value $R$ for the WTP measure of all consumers.
The demand in the local market is the summation of individual demands of all consumers ($\alpha n$) who exited conventional and joined the local market. It is dependent on the portion of consumers who choose to remain in the conventional market ($\alpha$) and the WTP of the average individual ($R$) for a good.

The demand can be written in terms of quantity demanded:

$$Q_L = \sum_{i=1}^{\alpha n} q_i = \sum_{i=1}^{\alpha n} \alpha n(A + RB - BP_L)$$ (2.24)

This equation can be rewritten in terms of price of the local good:

$$P_L = \frac{A + RB}{B} - \frac{1}{\alpha n B} Q_L$$ (2.25)

In both equations, the subscript "L" represents local. To signify non-local (also called "conventional" goods) the subscript "C" is used.
<table>
<thead>
<tr>
<th>Table 2.3. Welfare Equations in the Differentiated Market</th>
</tr>
</thead>
</table>
| **PS\textsubscript{local}** | \[
\frac{1}{2} \left( \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \left( kD \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \] |
| **CS\textsubscript{local}** | \[
\frac{1}{2} \left( \frac{A + RB}{B} - \frac{\alpha nA + \alpha nRB}{kD + \alpha nB} \right) \left( kD \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \] |
| **CS\textsubscript{conv}** | \[
\frac{1}{2} \left( \frac{A}{B} - \frac{\alpha nA + \alpha nRB}{kD + \alpha nB} \right) \left( n(1 - \alpha)(A - BP\textsuperscript{M}) \right) \] |
| **TW\textsubscript{diff}** | \[
\frac{1}{2} \left( \frac{A}{B} - \frac{\alpha nA + \alpha nRB}{kD + \alpha nB} \right) \left( n(1 - \alpha)(A - BP\textsuperscript{M}) \right) + \left( \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \left( kD \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \] |
| **\Delta TW\textsubscript{diff}** | \[
\frac{1}{2} \left( \frac{A}{B} - \frac{\alpha nA + \alpha nRB}{kD + \alpha nB} \right) \left( n(1 - \alpha)(A - BP\textsuperscript{M}) \right) + \left( \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \left( kD \frac{\alpha nA + \alpha nRB}{kD - \alpha nB} \right) \left( \frac{A}{B} \left( \frac{A}{B} \frac{BP\textsuperscript{M}}{kD + \alpha nB} \right) + kD \left( \frac{BP\textsuperscript{M}}{kD}\right)^2 \right) \] |
Table 2.3 shows the equations for all welfare measures in the differentiated model. The fraction of the consumers who transition to the traided market \((\alpha)\), the number of producers \((k)\), and the number of consumers \((n)\) all have the potential to impact the sign and magnitude of welfare changes after differentiation.

If producer welfare is increased by differentiation the following will hold true:

\[
PS_u < PS_L + PS_C
\]  

(2.26)

The welfare of the consumers will increase after differentiation if the following holds:

\[
CS_u < (CS_L + CS_C)
\]

(2.27)

Total market welfare is then represented as:

\[
(CS_u + PS_u) < (PS_L + CS_L + CS_C)
\]

(2.28)

There are a few things to note about these welfare measures and what may impact them. In the differentiated market, \(R_i\), the willingness-to-pay of an individual, impacts both producer and consumer surplus. A and B measures are consistent between the models and will not affect welfare outcome. The proportion of consumers who exit the conventional market to join the local market will effect the conventional as well as local markets.

Since the WTP of the average individual \((R_i)\), it is important for producers to know what price premium may result from the average WTP and market conditions. In the following section, I explore WTP, including how it is formed and specific estimates for Maine, in the following section.
2.6 Willingness-to-Pay for Local Goods

As discussed in the previous sections, one of the key factors for estimating welfare changes under differentiation is the magnitude of willingness-to-pay for a good. In this section I will be discussing willingness-to-pay estimates from a survey of Maine consumers and a more general examination of WTP estimates from the literature. Because willingness-to-pay for food traits is a common area of study with an expansive literature, I am going to be focusing on traits for goods that are either common agricultural products in the state of Maine or goods that are from studies conducted within the Northeast.

<table>
<thead>
<tr>
<th></th>
<th>Farms</th>
<th>Sales ($1,000)</th>
<th>Percentage Total Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total sales</td>
<td>7,600</td>
<td>666,962</td>
<td>100</td>
</tr>
<tr>
<td>Vegetables, melons, potatoes, and sweet potatoes</td>
<td>1,448</td>
<td>221,265</td>
<td>33.2</td>
</tr>
<tr>
<td>Milk from cows</td>
<td>286</td>
<td>134,560</td>
<td>20.2</td>
</tr>
<tr>
<td>Nursery, greenhouse, floriculture, and sod</td>
<td>965</td>
<td>71,401</td>
<td>10.7</td>
</tr>
<tr>
<td>Aquaculture</td>
<td>81</td>
<td>64,070</td>
<td>9.6</td>
</tr>
<tr>
<td>Fruits, tree nuts, and berries</td>
<td>1,149</td>
<td>51,510</td>
<td>7.7</td>
</tr>
<tr>
<td>Other crops and hay</td>
<td>2,552</td>
<td>44,867</td>
<td>6.7</td>
</tr>
<tr>
<td>Cattle and calves</td>
<td>1,253</td>
<td>26,423</td>
<td>4.0</td>
</tr>
<tr>
<td>Poultry and eggs</td>
<td>1,541</td>
<td>16,683</td>
<td>2.5</td>
</tr>
<tr>
<td>Grains, oilseeds, dry beans, and dry peas</td>
<td>307</td>
<td>16,220</td>
<td>2.4</td>
</tr>
<tr>
<td>Other animals and other animal products</td>
<td>489</td>
<td>7,972</td>
<td>1.2</td>
</tr>
<tr>
<td>Sheep, goats, wool, mohair, and milk</td>
<td>730</td>
<td>4,596</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Figure 2.9. Breakdown of Maine Agricultural Products

As seen in Figure 2.9, over half of Maine’s agricultural sales come from a mix of vegetables, melons, potatoes, sweet potatoes, and milk from cows. Using this, we can narrow down the WTP literature and show a sample of estimates that focus on the
willingness-to-pay for a "local" trait for goods that are either commonly produced in Maine or from studies within the Northeast.

One particularly useful estimation comes from the Atlantic Corporation, who conducted a survey in the early stages of the pandemic that included estimates of WTP for local-traited foods. During this time, supply chain issues and hoarding behaviors left many grocery stores with empty shelves and many consumers were thinking about agricultural goods and the food supply chain in unprecedented ways.

The study surveyed 503 Maine residents and was reweighted to be more representative of the sociodemographics of Maine (Corporation, 2020). As seen in Figure 2.4, point estates of WTP for local foods are somewhere between 17 and 23%. Focusing on Maine’s top products: fruits, vegetables, and dairy, the mean WTP estimates fall between 20 and 22%.

<table>
<thead>
<tr>
<th>Fruits</th>
<th>Vegetables</th>
<th>Dairy</th>
<th>Grains</th>
<th>Meat/Poultry</th>
<th>Seafood</th>
<th>Value-Added</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean WTP</td>
<td>20%</td>
<td>22%</td>
<td>20%</td>
<td>16%</td>
<td>23%</td>
<td>21%</td>
</tr>
</tbody>
</table>

Table 2.4. Maine Willingness-to-Pay Estimates for Local Foods (Corporation, 2020)

The mean WTP estimates from Atlantic Corporation have the potential to not be representative of the true mean WTP in "normal" times, due to the impact of the COVID-19 pandemic on consumer preferences. To investigate this possibility, I select WTP estimates for similar goods from the WTP literature for comparison.
<table>
<thead>
<tr>
<th>Authors</th>
<th>Study Area</th>
<th>Product</th>
<th>Estimated WTP (% premium)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Loureiro &amp; Hein, 2002)</td>
<td>Colorado</td>
<td>Potatoes</td>
<td>9.3%</td>
</tr>
<tr>
<td>(Carpio &amp; Isengildina-Massa, 2009)</td>
<td>South Carolina</td>
<td>Produce and animal products</td>
<td>27.5% (using a normal distribution)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>26.4% (using a lognormal distribution)</td>
</tr>
<tr>
<td>(Costanigro et. al, 2011)</td>
<td>Colorado</td>
<td>Apples</td>
<td>29.5-59.0% (depending on apple variety)</td>
</tr>
<tr>
<td>(Darby et. al, 2008)</td>
<td>Ohio</td>
<td>Strawberries</td>
<td>18% (grocery shoppers); 26% (farmers market)</td>
</tr>
<tr>
<td>(Giraud, Bond &amp; Bond, 2005)</td>
<td>Maine, New Hampshire, Vermont</td>
<td>New England specific specialty foods</td>
<td>13.2% for a $5 local good</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>10.5% for a $20 local good</td>
</tr>
<tr>
<td>(Li et. al, 2020)</td>
<td>Delaware</td>
<td>Oysters</td>
<td>11.3% for locals</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>37.2% for tourists</td>
</tr>
<tr>
<td>(Nganje, Hughner, &amp; Lee, 2017)</td>
<td>Arizona</td>
<td>Carrots and spinach</td>
<td>12.0% for carrots</td>
</tr>
<tr>
<td>(Wägeli et. al, 2015)</td>
<td>Germany</td>
<td>Milk</td>
<td>8.3% for spinach</td>
</tr>
</tbody>
</table>

Table 2.5. Willingness-to-Pay Estimates from the Literature

From the WTP estimates listed in Figure 2.5, we can see that the selected WTP estimates are within a range from 8% to 59%, with the majority of estimates falling within the 10% to 30% range. The estimates from Atlantic Corporation are within these bounds, and thus, are not unrealistic and may have not been significantly impacted by the COVID-19 pandemic.
2.6.1 Moving Beyond Local

The local trait is only one of many process-created traits. Two other common traits are non-genetically modified (non-GMO) and certified organic goods. Up to this point, I have mostly considered traits exclusively. It’s important to note that a product is not confined to exclusively one trait. In fact, sometimes the existence of one trait implies the existence of another (whether or not that trait is marketed). For example, one requirement of organic certification is the use of non-GMO seeds. Therefore, all organic foods are inherently non-GMO. In this case, selling a traitsed good as non-GMO is as simple as a marketing change. However, if a conventional grower wanted to market non-GMO crops they would need to change production inputs. Three of the most common traits (organic, non-GMO, and local), can occur concurrently in goods as seen in Figure 2.10.

![Figure 2.10. Trait Combinations](image)

Figure 2.10. Trait Combinations
Figure 2.11. Cost Curves for Shifting to Organic Production

Unlike local traited goods, not all traits can be differentiated from a simple marketing change; many require a substantial change to the production process. While marketing changes might have minimal impacts on the supply curve, because they do not impact inputs, other differentiations such as organic certification do require input changes.

Organically certified foods have both a fixed cost for the certification itself as well as required input changes necessary to meet the terms of the certification. Figure 2.11 shows the cost curves of a producer in the market producing conventional foods, including their shut down point \((Q_1, P_1)\) and break-even point \((Q_2, P_2)\). Both the introduction of the new fixed certification cost (center) and new input costs (right) cause an outward shift of both the break even point and the shut down point.

The magnitude of the shift observed in Figure 2.11 depends on the specific costs associated with the change, which vary between products. For this reason, it is important that producers investigate costs specifically applicable to their production to determine how their inputs and fixed costs may change. For example, Figure 2.12 shows that organic livestock and poultry suppliers face steep costs for organic certification. For that reason,
Maine’s dairy producers may want to enter certification with more hesitance than a vegetable farmer; although, these producers may also be able to sell their goods at a higher price premium than produce, so it is still a production change worth considering.

<table>
<thead>
<tr>
<th></th>
<th>Count Farms</th>
<th>Total Cost for Maine</th>
<th>Average cost per farm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organic Certification Expense</td>
<td>456</td>
<td>$798,000</td>
<td>$1,750</td>
</tr>
<tr>
<td>Organic Feed Purchased for</td>
<td>130</td>
<td>$11,731,000</td>
<td>$90,238</td>
</tr>
<tr>
<td>Livestock and Poultry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seed, Seedlings, and Planting</td>
<td>306</td>
<td>$1,453,000</td>
<td>$4,748</td>
</tr>
<tr>
<td>Stock</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2.12. Sales Value/Expenses of Producing Organic Foods, (USDA, 2019)

Most of Maine’s total sales value of organic goods come from operations making $500,000 or more a year (Figure 2.13). Because of the high fixed and variable costs, it would make sense for growers to be more incentivized to switch to organic production if they are larger growers than small growers.

Figure 2.13. Total Sales Organic in Maine in 2017 by Farm Sales Value
2.6.2 The Potential Impact of Changing Preference

For the purposes of this chapter, preferences have been treated as static. The utility functions used in the RUM framework earlier in the chapter compare the utility obtained from a traited and conventional good at a given time. The utility function is a reflection of consumers’ preferences, including the information that consumers are exposed to. What happens when this information changes/is incorrect?

Earlier, I discussed that the COVID-19 pandemic had driven demand for local foods higher. In the aforementioned Atlantic Corporation survey, individuals were asked to rate how strongly they agree with the following statements regarding beliefs/motivations about local food:

1. Local/direct to consumer channels have more available stock.

2. It is safer to shop local.

3. Shopping local supports local producers

The column of particular interest is the question pertaining to the safety of local foods, shown in Figure 1.2. Nearly 90% of consumers are either neutral or agree at some level with the statement that local food is safer than that from traditional retailers.
As mentioned earlier in the chapter, research has shown that local foods have been associated with higher safety risks than commercial retailers, despite the belief of consumers that the opposite is true (Butu et al., 2020). The discrepancy between consumer belief and objective information is not isolated to this specific example. There are many common beliefs surrounding traited foods that are rooted in misinformation. This
misinformation (as well as objectively true information) may be learned by individuals through social learning or through their own experience with a traited good. As a result, individuals update their preferences, ultimately resulting in demand changes.

In reality, preferences are constantly evolving as consumers gain new information. This means that while farmers may make a choice that is well justified given the current market, they also need to consider future preferences. This interaction is be shown in Figure 2.15. Past and current consumer interest spurs producers to enact production changes. Consumers then interact with the new goods and adjust their preferences. The process then starts over and continues cycling.

![Figure 2.15. Local Market for Undifferentiated Good, Adapted from (Goodhue, 2011)](image)

Figure 2.15. Local Market for Undifferentiated Good, Adapted from (Goodhue, 2011)

I use this dynamic approach to preferences in the next chapter to create an agent based model (ABM) to model how demand for local food is impacted by preference evolution.
CHAPTER 3
MODELING EVOLVING PREFERENCES AMIDST VARYING LEARNING CONDITIONS

3.1 Introduction

In the previous chapter, I discussed the welfare implications of the creation of differentiated goods markets. In this chapter, I examine how consumer preferences are formed and may change. Particularly, I examine the evolution of preferences through learning and discuss how this learning process may affect welfare outcomes in the market moving into the future.

The estimation of welfare under differentiation that was set up in the previous chapter is based on the theory that individuals derive some satisfaction, called utility, from consuming goods and that this utility allows them to rank bundles of goods. Discrete choice modeling in particular relies upon random utility modeling. Utility models are used to simplify complex behavior. As with any mathematical simplification of real-world behavior, these models may be imperfect. However, the use of utility theory is still fundamental to much of preference and choice modeling.

One specific criticism of utility theory was outlined in a paper from over 60 years ago that focused on the faults in "the assumption that the individual consumer allocates expenditures on commodities as if he had a fixed, ordered set of preferences described by an indifference map or by an ordinal utility function which he maximizes subject to restraints imposed by the money income he receives and the prices he must pay" (Basmann, 1956). While consumer demand theory uses the ceteris paribus assumption to
justify constant preferences at a given time, the attention on how preferences may change over time has not entirely diminished.

For food demand specifically, there has been a growing drive to consider dynamic preferences, particularly in wealthier economies such as the U.S. There is a growing sense that consumer food choice is dictated not solely for subsistence but also to satisfy higher level needs (Senauer, 2001). One particularly interesting argument behind this cultural shift as presented by Senauer is a result of a shift within Maslow’s hierarchy of needs. The argument states that U.S. citizens (specifically those of middle-class income and up) are no longer using food to fulfill base needs but are also using food to fulfill psychological needs. This shift is represented in Chapter 2 where I chose to model consumers as factoring non-market, values-based attributes such as environmental benefits, biodiversity benefits, and worker conditions into their purchase decision. In the case of my model, the purchase decision is for a marketable good in addition to the non-marketable attribute.

How preferences, the ranked ordering of goods by an individual consumer, change is notoriously difficult to model. In this chapter, I view preferences in the same light as the previous chapter, but I now consider implications to the market if an individual’s utility function changes over time as well as how choice outcomes change as the inputs (particularly information) to an individual’s utility function change over time. I utilize sociological and psychological lenses to examine the economic problem. The evolution of preferences is a learning process, which I will examine through a variety of theories and methods of evaluation. In this chapter, I build an agent-based model (ABM) to better understand how preferences are communicated and what implications these changing preferences have for market demand. Within the model, food purchasers (agents) adapt
their preferences, as captured by their willingness-to-pay, for local foods through experiential and social learning.

For explaining preference evolution, I use Alphabet Theory. The theory attributes changes of attitude to demographics, context, and the learning (or information exposure) process which are constantly changing with experience. In this theory, attitudes and context inform habits, which ultimately inform behavior. Alphabet Theory has been used to characterize organic and local food preferences (Zepeda and Deal, 2009). Behavior changes (food purchases) may result from changes in any of the variables influencing attitude. The two key foundations of preference from this theory that are most relevant to my model are information exposure and experience. Within my model, information exposure happens through social learning and information shocks. Food purchasers in the model also learn through experiential learning.

One particular aspect of preference change that I focus on is the market preference change resulting from information shocks to the system. These shocks are made to represent a variety of market-wide information exposures that could include bacterial outbreaks in the food supply, a widespread marketing campaign, or the COVID-19 pandemic. The impacts of the pandemic, in particular, are relevant due to its ongoing effects to the food system. The COVID-19 pandemic has upended American life. As stated in the first chapter, initial studies have found that COVID-19 has resulted in an increased demand for local foods (Grashuis et al., 2020). Within my ABM, I explore how the long-term effects of the shock changes under various conditions.

I also discuss the implications that widespread misinformation may have on the market. One interesting case of misinformation comes from research within the COVID-19
pandemic showing that an increased demand for local food during the COVID-19 pandemic is due to perceived health and safety risk reduction. In reality, while the collection of local food may be less likely to expose an individual to the virus than conventional markets due to the fewer people present, local food production has historically been found to be less safe than conventional, store-bought food (Butu et al., 2020).

The gap that forms between subjective belief and objective information, as illustrated by consumers believing that local food is safer when studies have shown otherwise, is an interesting phenomenon that is not unique to this particular information shock. Other beliefs that inform preferences may be influenced by misinformation. Misinformation is particularly prevalent within the market for traited goods. This is highlighted in a study by the Pew Research Center that finds that 55% of Americans believe organic food is better for health than conventional food, and 39% of Americans believe that genetically modified foods are worse for health than conventional foods (Hefferson and Anderson, 2016). While organic food may have less pesticide residue than conventional food, their nutrient densities have been found to be largely the same (Williams, 2002). Similarly, the literature for GM foods has largely discredited any linked hazards or nutrient density degradation to genetically modified foods (D’Agnolo, 2005).

I combine these considerations to create an agent-based model which helps explain how preferences might change under various conditions and what this could mean for future market demand and welfare.
3.2 Learning Theories and Applications

"I believe that (the) educational process has two sides—one psychological and one sociological. . . Profound differences in theory are never gratuitous or invented. They grow out of conflicting elements in a genuine problem."

- John Dewey (Dewey, 1897)

Before I begin explaining my agent-based model, it is important to review prominent learning theories that are foundational to the mechanisms in my model. The learning literature is vast and, for this reason, I narrow my focus to theories that are specific to adult learning since my model contains adults capable of making food choice decisions.

As noted by John Dewey in the preceding quote, the reason that many theories of learning exist is because learning itself is an intricate process that is difficult to model. Learning may affect how we think, feel, and act. In the case of food choice, learning affects food purchasers’ decisions through the evolution of preferences. There exist many types of learning styles and theories. Most modern learning theories include aspects of both experiential learning and social learning in knowledge formation. Modern learning theories have been the result of bridging works between disciplines such as psychology, sociology, neuroscience, philosophy, and others.

The concept of learning, of gaining knowledge through experience, study or imitation, is deeply ingrained in everyday life yet has substantial inconsistencies in its interpretation across fields. The concept of studying learning itself is not new, as it has been a source of debate for millennia. In the Western world, we know that famous Greek philosophers such as Socrates, Plato, and Aristotle all had their own beliefs about learning (particularly, how
to learn most effectively), many of which have endured. For example, the Socratic
method—the general philosophy of learning through cooperative dialogue and
questioning—is still foundational in many institutions of higher education, particularly law
schools.

It can be difficult to narrow learning theories to focus on adult learners, as many
learning theories were created to model educational learning in schoolchildren as conducted
in a classroom. The importance of this research is clear because learning is what drives
cognitive and social development in children. Learning how to walk or fill in multiplication
tables, however, is significantly different from the learning of adults, who already have
developed skills, beliefs, and ideologies that may greatly impact how they learn (or if they
are even choose to learn at all). It wasn’t until the 1970’s that theorists more commonly
began creating learning theories that were specific to adults to account for these variations
(Merriam et al., 2006). Even within this literature, there is a large focus on more explicit
learning such as seminars or job training. This learning may be different from the type of
constant, potentially subconscious learning that adults undergo that affects choice
outcomes such as those in my model.

In this section, I will be examining key concepts and theories of adult learning. In
particular, I will focus on five traditional, all-encompassing theories/philosophies of
learning: behaviorism, humanism, cognitivism, social learning theory, and constructivism;
and four additional learning theories: andragogy, self-directed learning, transformational
learning, and experience learning. For clarity, the five traditional theories are more general
philosophies that underlie the additional learning theories.
3.2.1 Traditional Models of Learning

Within modern learning theories, there are five primary "umbrella" theories: behaviorism, humanism, cognitivism, social learning theory, and constructivism\(^1\) These theories are the underlying foundation for many individual learning theories. These umbrella theories are more akin to philosophies, orientations, or approaches. They explain how a particular mechanism is responsible for learning. The features that make each learning style unique rely on the answers to five key questions (Ertmer and Newby, 2013):

1. How does learning happen?
2. Which factors influence learning?
3. What role does memory play in learning?
4. How does the transfer of information occur?
5. What types of learning does the theory best explain?

3.2.1.1 Behaviorism

Generally, behaviorism is the concept that conditioning rather than conscious thoughts or feelings lead to changed behavior. In behaviorism, "learning" happens only through a change in behavior (Merriam and Bierema, 2013). Within my ABM, this would be the component of learning which is experiential, i.e. only through the behavior of purchasing local foods may someone learn to prefer local foods. Critics of behaviorism largely claim that behaviorism is an oversimplified model that does not account for the complexities,\(^1\)

\(^1\)For the purposes of this paper, I separate social learning theory from cognitivism. While the two are theories are often lumped together, they provide distinct insights that are fundamental to my model.
collective experiences, and free will of learners. The mechanical nature of behaviorism does not allow for the unpredictability of human behavior (Merriam and Bierema, 2013)

3.2.1.2 Humanism

Humanism provides a sharp contrast from behaviorism; while behaviorism focuses on subconscious behaviors as outcomes from stimuli or expected results, humanism focuses on conscious behavior as the result of the desire to acquire knowledge. This type of learning is typically "facilitated" rather than "taught" by teachers to self-directed students. This view largely differed from earlier views and was pioneered by visionaries such as the psychologist Abraham Maslow and the psychologist Carl Rogers starting in the 1950s. The driver of learning in humanism is the assumption that humans are self-actualizing beings who will work to fulfill their highest potential. Humanism is the foundation for three of the most fundamental learning theories: andragogy, self-directed learning, and transformative learning (Merriam and Bierema, 2013). Within my ABM, the mechanisms are too coarse to pinpoint the motivational aspects that underlie humanism; however it is not in contradiction with them.

3.2.1.3 Cognitivism

Cognitivism also grew in opposition to behaviorism. Cognitivism centers on the understanding that learning occurs as an unobserved mental process. Where behaviorism focused on a linear process in which stimuli/motivation leads to behavior, cognitivism recognizes the complexities of the learning process, including the use of prior knowledge in learning. Cognitivism also acknowledges the heterogeneity of processes within individuals'
brains and that learning processes will differ by level of development. A lot of research on
cognitivism is done by studying and modeling processes within the brain (Merriam and
Bierema, 2013). Similarly to humanism, while my model does not contradict cognitivism, it
does not specify it.

3.2.1.4 Social Learning Theory

Social learning theory draws from both behaviorism and cognitivism but introduces two
additional key elements: observational learning and mediational processes. Pioneered by
psychologist Albert Bandura, this learning theory includes the traditional aspects of
independent learning created within cognitivism and behaviorism, but introduces new,
observational learning that happens by obtaining information through viewing others.
Bandura also explains that whether or not a behavior is learned is controlled by four
"mediational" factors: attention, retention, reproduction and motivation. An individual
must be paying attention to the behavior, remember the behavior, be able to reproduce the
behavior, and be motivated to perform the behavior in order for this observational (or
social) learning to occur (Bandura, 1977). Social learning theory is the foundation for
social learning within my model, i.e. how agents adapt their preferences by
"communicating" with or "observing" their neighbors.

3.2.1.5 Constructivism

The fourth theory of learning is looser in definition and varies greatly from the other
three foundational learning theories. Constructivism houses many theories that rely on the
assumption that learning is simply constructing meaning from experience. In this learning
theory, individuals are viewed as already full of knowledge. In this case, learning is a human processing. This learning style is particularly notable because it was one of the first to explicitly state the impacts of sociocultural environment on learning (Merriam and Bierema, 2013). The concept of constructivism is integral to my mathematical model, where preferences at time $t$ are dependent on preferences at time $t-1$, and are therefore also dependent on the information gained during that previous time period.

### 3.2.2 Additional Models of Learning

The following models are four of many more, specific learning theories that currently exist. As stated previously, because learning is a fundamental process in so many disciplines, many theories exist. The narrowing of the theories was done to focus on those which most apply to my research and largely follows *Fundamentals in Adult Learning* (Merriam et al., 2006), a key work which effectively summarizes the literature.

#### 3.2.2.1 Knowles’ Model of Andragogy

In the late 1960’s and early 1970’s, educator Malcolm Knowles proposed his humanistic model of learning known as andragogy. The concept of the term was to separate it as a distinct and independent counterpart of pedagogy. The idea was that pedagogy is for children and andragogy is for adults. While the concept has faced some criticism of its ambiguity, it is still present within the literature (Loeng, 2018). It is important to note that while andragogy is considered a model of learning, it could more accurately be described as a profile of an adult learner, including whether or not a person is ready to
learn and the impact of the learning outcome on an adult learner. Andragogy is founded on 6 key principles (Knowles, 1973):

1. As a person matures, her self-concept moves from a dependent personality to that of a self-directing human being.

2. An adult grows an expansive reservoir of experience that serves as a rich resource for learning.

3. The readiness of an adult to learn is closely related to the developmental tasks of their social role.

4. Due to a shift in time perspective as people mature, from future of application to immediacy of application, adult learners are more problem centered than subject centered.

5. The most potent motivations are internal rather than external.

6. Adults need to know why they need to learn something.

There have been many papers written both in criticism and support of the ideas put forth by Knowles. It is also important to note the context in which this was written — nearly sixty years ago — and that societal changes may make some aspects obsolete. One common criticism of note is of the fifth principle. Generally, the fifth principle applies to experiential learning, however the criticism generally points to the topic of social learning and how this violates the principle. Another, broader criticism, is that Knowles’ picture of an individual learner who is "autonomous, free, and growth-oriented" disregards
demographic factors and does not apply to learning situations such as those mandated by work or society. There have also been criticism that there is insufficient research to support the validity of the existence of the six principles (Merriam, 2008).

In summary, Knowles principles may not hold up as well to current models of learning, but have been foundational in the creation of other models of learning.

### 3.2.2.2 Self-Directed Learning

Around the same time that Knowles was forming his theory of andragogy, a Canadian educator named Allen Tough was coming up with another humanistic theory initially called self-planned learning, which would later be known as self-directed learning. Self-directed learning is still a common theory. Tough built a lot of his assumptions on similar foundations as andragogy.

The general concept of self-directed learning is highlighted by Knowles’ first principle, that as a person matures they become less dependent and more self-directed. In the context of the twenty-first century, this may seem less groundbreaking than it was sixty years ago. In today’s world, most bookstores have entire sections dedicated to learning which we call "self-help" books. The existence of these section shows that individuals are constantly furthering their own learning outcomes.

Despite the general familiarity with the concept, it is important to clarify what constitutes self-guided learning, which may be modeled through the goals of self-directed learning, the process of self-directed learning, or the attributes of self-directed learners.

Models that strive to achieve the goals of self-directed learning fall into one of three catch-all goals.
1. To allow adult learners be more self-directed

2. To centrally foster transformational learning (discussed in the following subsection)

3. To promote freedom of learning and social action as key to self-directed learning

Self-directed learning models may also be reliant on the process of self-learning. Self-directed models of learning fall into either linear designs or interactive designs. The models produced by Tough and Knowles themselves were conceptually linear, meaning that the process occurred over time with learning remaining a constant presence over time. These models involved clear, linear "steps" that did not involve any interactions between a learner, their environment, and their own knowledge/learning. Other researchers soon began to propose models that were more interactive in nature. For example, Brockett and Hiemstra’s Personal Responsibility Orientation (PRO) model, which models self-directed learning outcomes as an interaction between an individual’s characteristics and their self-directed learning behaviors. (Merriam et al., 2006).

Lastly, models that are considered self-directed models of learning may be reliant on the characteristics of a self-learner. For example, Grow’s Staged Self-Directed Learning is a linear model that has four stages. Each stage represents the formation of new characteristics of the learner: 1) dependent 2) interested 3) involved 4) self-directed (Grow, 1991). Grow’s theory is that an individual may be capable of developing their ability to be a self-directed learner and, if so, will progress from stage one to stage four. However, he notes the importance of teaching to match the degree of self-direction of learners.
3.2.2.3 Transformational Learning

Transformational learning (also interchangeably called transformative learning) involves "effecting change in a frame of reference" (Mezirow, 1997). There have been many waves of theory within transformational learning. I will not be diving deeply into the literature, but will explore the general idea of transformational learning.

Transformational learning is based in both constructivist and humanistic theory and states that adults use their past life experiences to form worldviews that frame their decision making. New experiences add to this "store" of information and knowledge. A foundational assumption of transformational learning is that learners must be adults capable of discourse. This is notable, as it differentiates the learning model as adult-specific whereas many of the other models apply to both adults and children.

Four of the assumptions of transformational learning are (Briese et al., 2020):

1. Humans are inclined to accept information that reinforces their current views.

2. Views must be challenged in order to be changed.

3. New points of view are created by human-sought new experiences.

4. If these new experiences are repeated, they eventually change the human’s point of view. Attitudes and assumptions related to experiences are changed through reflection and discourse, transforming habits of mind.

The two key points of the four points above are that in order for transformational learning to occur, the frame of reference (i.e. the point of view, the accumulation of experiences) must be changed in order for individuals to change their "habits of mind" (i.e.
the behaviors and assumptions that they default to). Transformational learning is often (but not exclusively) associated with large life events such as job transitions, medical diagnoses, and losses.

3.2.2.4 Experience Learning

While experience learning is a characteristic of many learning theories (including several of the previous models) as opposed to a theory itself, its importance is significant both to the literature and to the creation of my model. There are many models explaining experience learning; I will be focusing on Kolb’s Experimental Learning Cycle and Jarvis’ Model of Learning to illustrate the concept.

Theorist David Kolb proposed that an individual needs to have four abilities to be an effective experiential learner: concrete experience (CE) abilities, reflective observational (RO) abilities, abstract conceptualizing (AC) abilities, and active experimentation (AE) abilities. This means that they must involve themselves in situations freely and without bias (CE), reflect on their experience from different points of view (RO), they must be able to synthesize their experience into personal theories (AC), and they must be able to use these theories to make decisions (AE). Kolb proposes that learners are cycling clockwise through the four skills. Whichever two skills an individual is best at determines their learning style from one of four: accommodating, converging, diverging, and assimilating (Kolb et al., 2001).
Figure 3.1. Kolb’s Experiential Learning Cycle (Kolb et al., 2001)

Educator Peter Jarvis created his own model for experience learning in response to finding the Kolb’s model insufficient. This model is simply referred to as the Jarvis Model. Jarvis built upon Kolb’s work by creating a model with nine experiential learning styles or "routes", including three routes that involved the individual choosing not to learn: presumption (the learner assumes they already know it), nonconsideration (the learner will not consider learning it), and rejection (the learner refuses to learn it). This model was more complex than Jarvis’ model of experiential learning and notably involved a more complex process (Merriam and Bierema, 2013). Within his model, an individual learning
experience could be modeled with the "whole" of the individual going in and the "whole" of
the individual, revised amidst learning, coming out at a later time (see 3.2. (Jarvis, 2006)

3.2.3 Mathematics of Learning

The application of learning theories is increasingly done through mathematical models,
including the use of machine learning. These models can be used, in turn, to predict
learning outcomes that can be helpful in applications from game theory to predicting
success of a curriculum. While many types of mathematical models for learning exist, I will be focusing on the DeGroot model because it is most similar to the mathematics used in my model.

DeGroot learning is a linear process. The premise of the Degroot process is that agents take the weighted opinions of their neighbors and update their own belief. While it may be criticized, it is still used throughout the literature (Molavi et al., 2018). In the DeGroot updating process (Eq. 3.1), the opinion (x) of an individual (i) on a given subject at a point in time (t) changes as they are exposed to a matrix (W) of the opinions of other agents, subject to a weighting of the trust of all other individuals (j) in the previous moment. (Golub and Sadler, 2016).

\[ x_{i,t} = \sum_j W_{ij} x_{j(t-1)} \] (3.1)

The learning processes within my model are simple linear processes where the opinions of an individual’s neighbors are weighted evenly and the adjustment to preferences in a given period is dependent on the preference of the individual from the previous round and the information that they are exposed to from their neighbor, given a probability and "strength" of learning. The "strength" of learning shows how readily an individual is to change their preference given new information.

3.2.3.1 Consumer Preference Evolution

In my agent-based-model, I model preferences as a time series updating process and assessing outcomes at static points in time.
Within the preference literature, there are several models for explaining preference formation and learning. One model growing in prevalence is Alphabet theory, which combines other theories into a catch-all theory. Alphabet theory includes both Values-Belief-Norm (VBN) and Attitude-Behaviour-Context (ABC) theories (See 3.3).

For the purposes of my thesis, I examine learning within the context of consumption, specifically, discrete choices between food trait alternatives. For this reason, I focus on will be adults regularly making purchasing decisions. In the creation of my model, I draw primarily from behaviorism and social learning theory.
One way of examining the process of preference evolution is by adapting Jarvis’ Model to suit my ABM. In Figure 3.5, I have lumped the steps of Jarvis’ Model into "Experiential Learning" and added "Social Learning". This simplified adaptation shows the core linear process of my preference learning model. To detail specifically some of the mechanisms that I assume drive learning, see Figure 3.5.
3.3 Agent Based Model

To model learning behaviors, I use an agent-based model (ABM) to investigate how the process outlined in Figure 2.2 leads to emerging market-level trends. I first summarize the model then provide a more detailed Overview, Design concepts, Details (ODD) documentation formatting which is standard amongst ABM literature to explain my model.
3.3.0.1 Purpose

In the previous chapter, I discussed market-level consumer preference for local goods after differentiation of local goods; in this model I will be focusing on how varying learning conditions, information shocks, and misinformation may lead to emerging market level consumption trends. As established in the previous chapter, the average consumer preference of a market drives demand through the influence of preference on purchase decision. It is the aggregation of individual consumers’ preferences that impact the market at large. This is because individuals’ preferences are constantly adjusting under new information. The new information an individual learns may then affect the individuals around them through social learning. Because this is a problem examining market-wide outcomes that emerge from individual level learning behaviors, it is particularly well-suited for an agent-based model (ABM). I will discuss how trends that emerge from the simulations may model similar scenarios in differentiated markets.
The model is a closed market with 400 individuals. Each week, the individual first purchases a unit of local or conventional food. Individual preference is bounded between 0 and 1, with a preference less than 0.5 resulting in the purchase of conventional and greater than 0.5 resulting in a local food purchase. Individuals then learn based off of their experiences and communications with their neighbors within a radius of 20 units. They then adjust their preferences at a magnitude according to their learning probabilities, at a given "strength". Strength of learning refers how "extreme" learning is, i.e. a strength of 1 means that the individuals will perfectly imitate/adjust to full preference, and 0 means no adjustments will be made. Individuals are also subject to market-wide information shocks where information is presented which sways all consumers in the market to increase or decrease preferences. The basic flow of the model is shown in Figure 3.6. A total of 4,026 runs were simulated.
3.3.1 Research Questions

1. How do social and experiential learning amidst varying learning conditions affect overall market preference (and resulting market demand and welfare)?

2. To what extent might we expect shocks like the COVID-19 pandemic to persist/die out?

3. How does information and misinformation spread in the system, and what implications could this have on demand stability?

3.3.2 Model Structure

3.3.2.1 Entities, State Variables, and Scale

The agents in this simulation are people, assumed to be the individual in a household making a purchase decision for food. The agents undergo experience social or experiential learning in a round. The magnitude of their learning will depend on their social-strength and experience-strength. This will lead them to adjust their preferences and make a purchase decision each round. The number of people is fixed after the initial set-up and is meant to represent a closed community with no new members and no members leaving.

The main "currency", so to speak, in this model is preference for local foods (preference). Preference is bounded between 0 and 1, where 0 indicates the absence of preference for local food (the individual will never choose to consume local food) and 1 indicates a strong preference for local food (the individual will choose local food in all scenarios). Preference is adjusted by learning through an agent’s own experiences with local food, learning from other agents and adjusting to mis/information shocks.
There are ten people-own variables: histlocal, round-choice, preference, social-prob, experience-prob, social-strength, experience-strength, covid-shock, covid-shock-impact, and learning-style which are defined as follows:

- **histlocal**: Histlocal is the number of local food items an individual has purchased over the course of the simulation.

- **round-choice**: Round-choice shows whether the individual chose to consume local (1) or conventional food (0) in a given round. This is important for simulations using the experience learning function that requires consumption of a local food for learning to occur.

- **pref**: The preference variable represents individuals’ inclination to purchase local food. Preference ranges between 0 and 1, with preference = 0 indicating no preference for local food and preference = 1 indicating a preference for local food. A preference $\geq 0.5$ indicates a preference for local food that will end in a purchase decision (meaning that the individual will choose to consumer local food that tick); preference $< 0.5$ indicates a preference for conventional food/indifference to local food (meaning that the individual will choose to consumer conventional food that tick).

- **social-prob**: This is the probability that an individual will undergo social learning in a round. The probability is is a number between 0 and 1 and is compared to a randomly drawn number to determine whether the individual undergoes learning in a given round.
• **experience-prob**: This is the probability that an individual will undergo experiential learning in a round. The probability is a number between 0 and 1 and is compared to a randomly drawn number to determine whether the individual undergoes learning in a given round. If the experience learning is in a "locals-only" setting, this also is dependent on round-choice.

• **social-strength**: This shows how fully an individual adapts to the preferences of their neighbors. This is bounded between 0 to 1, with a strength of 0 indicating that an individual will not imitate, and a strength of 1 indicating that an individual will imitate exactly.

• **experience-strength**: This shows how fully an individual adapts to the preferences to match their experience. This is bounded between 0 to 1, with a strength of 0 indicating that an individual will not imitate, and a strength of 1 indicating that an individual will imitate exactly.

• **covid-shock**: This shows whether a given simulation will have a covid-shock, including the number of shocks, ranging between 0 and 3 shocks per round.

• **covid-shock-impact**: The impact of the shocks is similar to the learning strengths and shows how deeply it affects people in a simulation round. Similar to learning strengths, this is bounded between 0 to 1, with a strength of 0 indicating that an individual will not imitate, and a strength of 1 indicating that an individual will imitate exactly.
There are 2 learning styles in the model: models and conformist. Conformist learning is when an individual conforms to the mean of the agents within a radius r whereas models is where an individual will choose a model to conform to.

The stopping condition is set at 260 ticks. This is a simulation which could theoretically continue forever so I chose a cut off that seems reasonable in line with linear time and the time frame of forecasting agricultural producer decisions. There is one tick per purchase. Assuming that each person is buying the food for their household once per week, this simulates a 5 year change in the preferences within this community. The model was varied over the values shown in Figure 3.7.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Values Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>shock-impact</td>
<td>The magnitude that a shock impacts an individual’s preference</td>
<td>0, 0.25, 0.5, 0.75, 1</td>
</tr>
<tr>
<td>number-shocks</td>
<td>How many market-level information shocks happen in a simulation</td>
<td>1, 2, 4</td>
</tr>
<tr>
<td>shocktype</td>
<td>“conv” – Shocks lower preferences, making consumers more likely to purchase conv. “local” - Shocks raise preferences, making consumers more likely to purchase local</td>
<td>“conv”, “local”, “random”</td>
</tr>
<tr>
<td>social-strength</td>
<td>The magnitude that a social interaction impacts an individual’s preference</td>
<td>0.25, 0.5, 0.75, 1</td>
</tr>
<tr>
<td>social-prob</td>
<td>The probability that an individual learns socially</td>
<td>0, 0.5, 1</td>
</tr>
<tr>
<td>experience-strength</td>
<td>The magnitude that an experience impacts an individual’s preference</td>
<td>0.25, 0.5, 0.75, 1</td>
</tr>
<tr>
<td>experience-prob</td>
<td>How likely an individual is to undergo experiential learning</td>
<td>0, 0.5, 1</td>
</tr>
<tr>
<td>experience-learn-type</td>
<td>“stochastic” – An individual can have a preference-adjusting experience with both local and conventional goods “only-local” – An individual can only experience learn if they consume local foods in a round</td>
<td>“stochastic”, “only-local”</td>
</tr>
</tbody>
</table>

Figure 3.7. Table of Simulation
3.3.3 Process Overview & Scheduling

The basic premise of the model is that people make a purchase decision based off of their current preference, learn from their neighbors, learn independently, and adjust their preference. They repeat the process once every tick. Additionally, individuals will adjust their preference as the community experiences a COVID-19 shock. Each round the colors of the people change to reflect their changed preference.

3.3.4 Design Concepts

Within the simulation, the people utilize social learning by adjusting their preferences based off of what they learn from their neighbors, independent learning, and from mis/information shocks. The learning styles are uniform across all people for each simulation in both learning styles. The "models" learning styles involve the people choosing one person from whom they learn and model their own preference after. The "conformist" learning styles involve the people learning from a group and modeling their own preference after the mean of the group. The learning style remains the same over the duration of the run and the same learning style is used for social learning.

There are several outputs that I will be monitoring. First, the preference distribution over time is monitored. The max, min, standard deviation, and mean preference are monitored over time. Additionally, the simulation-long tally of local food purchase decisions show emergent trends in community-wide preferences. This is unique as it shows how preferences have changed over time.
3.3.4.1 Mathematical Framework for the Agent-Based Model

The evolution of preferences in my agent based model takes the form of a linear, time series updating process (Equation 3.2). In this process, I model the evolution of a preference parameter, $p$. This parameter is going to capture the comparison between the utility obtainable from an untraited good and a traited good. If $p$ is below a given threshold, the decision-maker will choose to consume the traited good. If $p$ is above some threshold, the decision-maker will choose to consume the traited good.

$$p_{i,t+1} = p_{i,t} + I_{s,t}S_{i,t} + I_{e,t}E_{i,t} + \delta - \zeta$$  \hspace{1cm} (3.2)

Where the preferences of individual (i) in the subsequent time period (t+1) is dependent on the preference of the individual in the current time period ($p_{i,t}$) plus an adjustment (if $I_s = 1$) from social learning ($S_{i,t}$), an adjustment (if $I_e = 1$) from experiential learning ($E_{i,t}$) and is subject to two truncation conditions, which keep the preference between 0 ($\delta$) and 1 ($\zeta$).

$$I = \begin{cases} 
1, & \text{if learning (social (s) or experiential (e)) happen at time } t \\
0, & \text{if otherwise}
\end{cases}$$  \hspace{1cm} (3.3)

$S$ represents the adjustment to preferences for individual at time $t$ for social learning, where $\theta_s$ is the strength of learning. $E$ represents the adjustment to preferences for individual at time $t$ for experiential learning where $\theta_e$ is the strength of experiential
learning. An important note - within this model, social learning can happen no matter the purchase decision in a round, but experiential learning can only happen when a round’s decision is to purchase local food.

\[ S_{i,t} = \theta_s(\bar{p} - p_{i,t}) \]

\[ E_{i,t} = \begin{cases} \theta_e(1 - p), & \text{if } M_{i,t} = 1 \\ -\theta_e(p) & \text{if } M_{i,t} = 0 \end{cases} \]  
(3.4)

\[ \bar{p} \text{ is the population mean of individuals in radius } r \text{ (shown in 2.5 below)} \]

\[ \bar{p}_t = \frac{1}{n} \sum_{i=1}^{n} p_i \subseteq n \text{ in radius } r \]  
(3.6)

M is a binary indicator variable that shows if an individual/agent has a positive experience with local food (M=1) or a negative experience (M=0). This applies to both learning through experience with local food and stochastic learning. M will be equal to one if the probability (Pr) that individual i at time t is greater than a randomly generated number (x) exclusive to individual i at time t, selected from a uniform distribution between 0 and 1. If the

\[ M_{i,t} = \begin{cases} 1 & \text{if } Pr_{i,t} > x_{i,t} \in [0,1] \\ 0 & \text{if } Pr_{i,t} < x_{i,t} \in [0,1] \end{cases} \]  
(3.7)
δ and ζ are truncation conditions that keep (this is because \( p \in [0,1] \)) (See A.1 and A.2 in Appendix for these conditions).

This mathematical model is the theory underlying the coded processes in my agent-based model.

### 3.3.5 Initialization

The world sets up by creating the meeting place (seen as gray patches in the interface) and the people who are made in a range of high preference (green), medium preference (pale green), low preference (orange) and no preference (red). The people are randomly distributed (see Figure 3.8). A slider on the interface controls the number of people in the simulation and the radius for social learning. The probabilities and strength for both experiential and social learning as well as the learning (both social and experiential) are able to be changed. The covid-shock-impact and the presence of COVID-19 shocks are also included.
3.4 Analysis

Over the simulations ran, I recorded mean, standard deviation, max, and min of preference amongst agents. I also recorded how many units of local food had been acquired by the population over the course of the simulation. I also recorded how many individuals chose to consume local within each given round. Figure 3.9 shows the interquartile range for the three outcome variables: standard deviation of preference at the end of the simulation, mean preference at the end of the simulation, and total local food purchase decisions at the end of the simulation.
Figure 3.9. Interquartile Range Outcome Variables

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>N = 4,014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience learning mechanic</td>
<td>2,007 (50%)</td>
</tr>
<tr>
<td>Mean preference</td>
<td>0.49 (0.38, 0.50)</td>
</tr>
<tr>
<td>Std. Dev. preference</td>
<td>0.11 (0.00, 0.28)</td>
</tr>
<tr>
<td>Total local purchases</td>
<td>51,297 (1,163, 52,062)</td>
</tr>
</tbody>
</table>

Figure 3.10 show how the distribution of preferences changed over the course of the simulation. The mean preferences at time 0 followed a normal distribution (note: one count on the histogram represents the mean preference for the entire population in one simulation run). The distribution of preferences went from a normal distribution to left-skewed. The skew is due to the "only-locals" learning style. This experiential learning style requires individuals to have experience with local food in a given round in order to adjust their preferences. Assuming that not all individuals have a positive experience, without the added component of social learning, preferences will quickly devolve to below 0.5 because people are unable to experience the good and thus adjust their preferences.

Although the previous figures may give information about mean preferences, they do not account for the distribution of preferences within a given simulation run. Now, examining the standard deviation shown in Figures 3.11-3.13, two interesting trends show up. First, a large number of models move to a standard deviation of 0 by halfway through
the simulation. Preferences are converging. However, a seemingly random smattering of standard deviations appear to be steady and non-zero. This is particularly interesting because it means that there are states in which simulations are not converging.

One of the most interesting outcomes was the effect of the "Experience" learning process. There were two different experiential learning types tested: a stochastic learning process where individuals randomly adjust their preference and another where individuals only adjust their preference if they have an experience with local goods in a specific round. The second learning style follows the basic idea of differentiation where the local food is a "new" good within the market. Following the logic of behaviorism, an individual should
only be able to adjust their preferences through experiential learning by consuming local food. For that reason, experiential learning only occurs when local food is acquired in a specific round. Using this framework, if social learning does not exist, preferences will eventually devolve until all of the population has a preference less than 0.5. This is because people cannot communicate their positive experiences and people with preferences less than 0.5 will not choose to purchase the good. This means, without social learning to balance, preferences of the population will always result in all people eventually reaching an equilibrium below 0.5.

Table 3.1. Comparing Social & Experience Learning

![Graph comparing social and experience learning](image)

From anecdotal experience, it is unclear if this is an accurate representation of experiential learning. For that reason, I chose to also make an experience learning style that is stochastic, for comparison. The premise of this style is that if an individual can also learn from the non-local good (i.e. a negative experience with a non-local good can boost their preference to allow them to prefer local).
Figure 3.14. Shock Impact in Simulations with Low, Medium, and High Learning

While the coding for social and experiential learning is very similar, the differing results can likely be blamed on the "only-locals" experiential learning style. Examining the results over time as shown in Table 3.1, the difference in the trend between models with a strictly social learning mechanism and a “social plus experience” learning mechanism is fairly similar. The main differences are that including experiential learning leads to a lower mean preference and also leads to more outcomes away from the mean. It’s important to note that because any preference that is greater than 0.5 results in a purchase of local food, a system with a mean preference of 0.49 and a tight standard deviation may have the same number of conventional food purchases as one with a mean 0.

Results from the information shocks showed that learning had the biggest impact on the longevity of the shocks within the system. Above, three different simulation outcomes with similar variables apart from learning are shown. All three have a relatively high shock impact of 0.7 (meaning that the individuals will adjust their preference up to 70% of

<table>
<thead>
<tr>
<th></th>
<th>Low Learning</th>
<th>Medium Learning</th>
<th>High Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience learning</td>
<td>0.05</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td>probability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience learning</td>
<td>0.05</td>
<td>0.35</td>
<td>0.90</td>
</tr>
<tr>
<td>strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social learning</td>
<td>0.05</td>
<td>0.35</td>
<td>0.90</td>
</tr>
<tr>
<td>probability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social learning</td>
<td>0.10</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td>strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience learn-type</td>
<td>only-local</td>
<td>stochastic</td>
<td>stochastic</td>
</tr>
<tr>
<td>Shock impact</td>
<td>0.70</td>
<td>0.70</td>
<td>0.70</td>
</tr>
<tr>
<td>Number of shocks</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Shock Type</td>
<td>local</td>
<td>local</td>
<td>local</td>
</tr>
</tbody>
</table>
perfect preference for local food (preference = 1). Figure ?? has the highest learning probabilities and strengths. In this simulation, the shocks had almost no longterm impact and only a brief short term impact. Figure ?? shows a simulation of mid-range learning probabilities and strengths. Within this model, individuals have a fairly sustained shock impact, however it collapses back to previous mean preference over time. Figure ?? is arguably the most interesting trend. In this simulation with low learning probabilities and strengths, the shock is sustained and affects the outcome of the simulation.

### 3.4.0.1 Regression

To better understand the relationship between my independent variables and my dependent variable, I utilized the ordinary least squares (OLS) estimator to summarize the relationship between initial parameters and outcomes in the final time period.

I run regressions of the form:

\[
y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_2 \times X_3 + \beta_5 X_4 + \beta_6 X_5 + \beta_7 X_4 \times X_5 \quad (3.8)
\]

where the X variables represent the following (Figure 3.4.0.1):

| \( X_1 \) | Experience learning mechanics (learning by direct experience with local) |
| \( X_2 \) | Experience learning - probability |
| \( X_3 \) | Experience learning - strength of learning |
| \( X_4 \) | Social learning - probability of learning |
| \( X_5 \) | Social learning - strength of learning |
I used three different dependent variables when testing the model \( (y_t) \). I used mean preferences, standard deviation of preferences, and quantity demanded of local goods. Mean preferences are that of the population at the final time \( (t=260) \) in the model during simulation \( i \). Quantity demanded of local goods shows cumulative purchase decisions made over all time periods in simulation \( i \). Quantity demanded is the result of preference in each time but shows more of the dispersion of the preferences as well as how preferences may have changed over time. Standard deviation helps to show if the preferences of the population in the model converged or diverged over time.

<table>
<thead>
<tr>
<th>OLS Regression</th>
<th>Dependents variable:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Pref. St. Dev. of Pref. Quantity Demanded Local</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.110***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Exp. Learn Mechanics</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Experience Learning Probability</td>
<td>-0.014*</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Experience Learning Strength</td>
<td>-0.103***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
</tr>
<tr>
<td>Experience Learn Strength x Prob</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Social Learning Probability</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Social Learning Strength</td>
<td>0.038***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
</tr>
<tr>
<td>Social Learning Strength x Probability</td>
<td>0.409***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,014</td>
</tr>
<tr>
<td>R²</td>
<td>0.379</td>
</tr>
</tbody>
</table>

*Note: \( p<0.1; **p<0.05; ***p<0.01 \)

Figure 3.15. OLS Regression Output
The output from the OLS model reflects some of the earlier graphed trends discussed. Within the three dependent variables, mean preference and quantity demanded show market outcome and standard deviation shows how a parameter affects the dispersions of preferences within a given simulation. Experience learning when only done by consumers who have chosen local results in a mean preference of 0.123 less than a similar model with a stochastic mechanism. Interestingly, experience learning had a positive coefficient despite this trend whereas social learning had a negative coefficient. Experience learning of only local resulted in a higher standard deviation than that of stochastic learning. Notably, the impact of the shock has very minimal impact on the outcome of the model.

3.5 Misinformation in the Model

As discussed in the previous chapter, misinformation can greatly impact consumer preference. While this model does not identify objectively true and false information, it is interesting to note how social learning impacts the spread of information in individuals within a model. Using an adaptation of my model, I created a "bad actor" to represent misinformation. I then set experience learning to 0 in order to show the effects of this one bad actor on the system when social learning is present. As shown in Table 3.2, the preferences of the bad actor spread in the system first in waves then lead to the entire system devolving to match the bad actor. While this may be an extreme example, it does show the potential harm of misinformation on a social system, if the bad actor is spreading misinformation.
Table 3.2. Diffusion of Secondhand Misinformation
3.6 Conclusions

The most interesting result is the influence of learning on the impact of information shocks. In the model, the longevity of a shock such as the COVID-19 pandemic would depend very heavily on the learning in the system.

Learning facilitates changing preferences in two ways. Firstly, through both experiential and social learning it can slowly move preferences to a convergence point. Conversely, learning can also spread information through the system as shown in Table 3.2. Overall, learning can have large effects on the market outcome.

This is a model with simplified assumptions to show general trends in how food purchase decision and preferences change under the presence of social learning. The results show a need for producers to understand information transmission in their markets to make the most sensible production decisions.


APPENDIX

CHAPTER 2

δ is a truncation condition which sets the value of preference to 0 if the value of the adjusted preference is negative (this is because p ∈ [0,1])

\[
\delta = \begin{cases} 
0, & \text{if } (p_{i,t+1} + I_{s,t}S_{i,t} + I_{e,t}E_{i,t}) \geq 0 \\
(p_{i,t+1} + I_s * S_{i,t} + I_e E_{i,t}), & \text{if } (p_{i,t+1} + I_s * S_{i,t} + I_e E_{i,t}) < 0
\end{cases}
\]

(A.1)

ζ is a truncating condition which sets the value of preference to 1 if the value of the adjusted preference is negative (this is because p ∈ [0,1])

\[
\zeta = \begin{cases} 
0, & \text{if } (p_{i,t} + I_{s,t} * S_{i,t} + I_{e,t} * E_{i,t}) \leq 1 \\
((p_{i,t+1} + I_s * S_{i,t} + I_e * E_{i,t}) - 1), & \text{if } (p_{i,t+1} + I_s * S_{i,t} + I_e * E_{i,t}) > 1
\end{cases}
\]

(A.2)
<table>
<thead>
<tr>
<th>Experience learning probability</th>
<th>0.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience learning strength</td>
<td>0.35</td>
</tr>
<tr>
<td>Social learning probability</td>
<td>0.35</td>
</tr>
<tr>
<td>Social learning strength</td>
<td>0.35</td>
</tr>
<tr>
<td>Experience learn-type</td>
<td>only-local</td>
</tr>
<tr>
<td>Shock impact</td>
<td>0.70</td>
</tr>
<tr>
<td>Number of shocks</td>
<td>3</td>
</tr>
<tr>
<td>Shock Type</td>
<td>local</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experience learning probability</th>
<th>0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience learning strength</td>
<td>0.05</td>
</tr>
<tr>
<td>Social learning probability</td>
<td>0.05</td>
</tr>
<tr>
<td>Social learning strength</td>
<td>0.05</td>
</tr>
<tr>
<td>Experience learn-type</td>
<td>only-local</td>
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<tr>
<td>Shock impact</td>
<td>0.70</td>
</tr>
<tr>
<td>Number of shocks</td>
<td>3</td>
</tr>
<tr>
<td>Shock Type</td>
<td>conventional</td>
</tr>
</tbody>
</table>

Figure A.1. Conventional Shock with Low Learning Prob. / Impact

Figure A.2. Conventional Shock with Mid Learning Prob. / Impact
Lauren Miller grew up in Gillette, Wyoming, and attended the University of Wyoming to receive a B.S. in Economics and a B.S. in Environmental System Science before moving to Maine to pursue her graduate studies. She is passionate about agriculture in all of its many forms. Her research interests are motivated by the hope of an equitable food system and a climate resilient future. Lauren Miller is a candidate for the Master of Science in Resource Economics and Policy degree in School of Economics from the University of Maine in August 2021.