Reference price effects in consumer choice for protein
&
Impacts of subsidized pasture insurance on land value and use

by

Andrew Emery Anderson

B.S., Brigham Young University-Idaho, 2017
M.S., Purdue University, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2023

Abstract

Essay 1: Consumers have faced rapidly changing food prices in recent years—meat prices have been particularly volatile—leading individuals to be frequently surprised by the prices they encounter. In contrast to neo-classical assumptions, applications of prospect theory to consumer choice have hypothesized that consumers evaluate prices relative to a reference price, are loss averse, and experience diminishing sensitivity. Accordingly, I tested for reference price effects in consumer choice for protein and demonstrated the implications in post-estimation analysis. I leveraged choice experiment data in a random utility framework while progressively incorporating various reference price features and found that including reference price effects improves model performance, both within and outside of the estimation sample. The magnitude of reference price effects varies by product and across marketing channels, with implications for elasticity estimates, market share predictions, and welfare analysis. My results are consistent with previous research but adds an application to a previously unstudied product group across market channels, while also demonstrating the implications of various modelling approaches. This additional information provides insights into protein markets and important guidance to researchers and policy analysts.

Essay 2: Benefits of government subsidized farm programs may pass through the production sector to agricultural input prices. Likewise, publicly supported insurance programs can increase expected future revenue and reduce risk, thus altering production incentives and potentially impacting input prices and quantities. Accordingly, I examined the impact of Pasture, Rangeland, and Forage (PRF) Index Insurance on agricultural land values (price) and pastureland area (quantity). I leveraged the staggered rollout of PRF at the county level in a non-traditional Difference-in-Differences framework and found a positive effect on both farmland value and acres of pastureland. However, higher percentages of public land in a county are associated with

smaller effects on land value and larger effects on pasture area. My results are in line with previous research and provide additional detail on the geographical impact. This additional nuance gives policy makers localized insights into the distribution of program effects.

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Approved by:

Major Professor
Glynn T Tonsor

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Dedication

For Tyra Alene Anderson (1993-2022)

May we meet again after I have lived my allotted time, as you did so marvelously with yours.

And should we die before our journey's through
Happy day! All is well!
We then are free from toil and sorrow, too
With the just we shall dwell!
— William Clayton, "Come, Come Ye Saints"

Jesus said unto her, I am the resurrection, and the life:
he that believeth in me, though he were dead, yet shall he live:
And whosoever liveth and believeth in me shall never die.
— John 11:25-26

Chapter 1 - Reference Price Effects in Consumer Choice for Protein

Introduction

Consumers have faced rapidly changing food prices in recent years—meat prices have been particularly volatile—leading individuals to be frequently surprised by the prices they encounter. In January 2023 the United States Bureau of Labor Statistics (BLS) reported that its Consumer Price Index (CPI) for all items had increased by 6.3% over the previous 12 months, while the CPI for meat, poultry, fish, and eggs had risen 8.1% during the same period. Previously, in May and June of 2020 consumer meat prices spiked before falling dramatically, bottoming out in December 2020, only to rise again over the next two years (BLS, 2023a). Furthermore, individual protein commodities have experienced anomalous price shocks. These price dynamics were driven both supply shifts (e.g., COVID related closing of packing plants or animal disease outbreaks) and demand shifts (e.g., COVID related pandemic stockpiling or shocks to disposable income from government stimulus payments). During periods of unexpected price changes, consumers are often surprised by the prices they encounter (Lee, 2021). If consumers systematically alter their purchasing behavior in the presence of unexpected price changes, then accurately measuring the impact of these events may require accounting for consumer expectations regarding prices and the effect of surprises.

In contrast to neo-classical assumptions, applications of prospect theory to consumer choice have hypothesized that consumers evaluate prices relative to a reference price, are loss averse, and experience diminishing sensitivity. These models have their basis in adaption level theory from the field of psychology which holds that people evaluate choice criteria in a relative sense (Helson, 1964). This principle was formalized first into a model of choice under uncertainty before eventually being adapted for riskless settings, such as consumer choice (Kahneman et al., 1991; Kahneman & Tversky, 1979; Tversky & Kahneman, 1991). The distinguishing aspect of this choice framework is its basis in the prospect theory value function rather than a traditional utility function. There are three distinct features of the value function: reference dependence, loss aversion, and diminishing sensitivity. First, reference dependence implies that consumers evaluate prices[1] relative to a reference point, such that when consumers purchase at a price below (above) the reference point they experience a gain (loss) from the status quo. Likewise, loss aversion means that losses diminish value more than gains of equal magnitude improve it. Lastly, diminishing sensitivity means that the marginal utility (disutility) of a gain (loss) is decreasing with its size. Each of these features of the utility function have important effects on consumer behavior, which I refer to as reference price effects (RPEs) throughout this essay.

As a result of the size of protein markets as well as historical price volatility, the impact of RPEs on purchasing behavior may be economically substantial. Therefore, the objective of this study is to determine if RPEs explain consumer choice for protein and measure the resulting implications for markets. If consumers systematically deviate from the assumptions of traditional demand models, then the resulting economic predictions may be inaccurate. Admittedly, all models and "wrong" in that they simplify reality to some extent. However, my objective is to determine if failing to include RPEs causes demand models to be "importantly wrong" (Box, 1976). Therefore, after demonstrating the statistical basis for RPEs, I thoroughly demonstrate the impact of these modelling choices on various economic predictions.

---

[1] While we focus on prices in this essay, reference dependence and loss framing can be applied to any choice criteria that the consumer evaluates.

To accomplish the objective of this essay, I leveraged choice experiment data in a random utility framework while progressively incorporating various reference price features and found evidence in favor of reference price effects. First, I specified a series of multinomial logit models in a random utility framework, taking as the baseline a standard linear price effect. Additional models each incorporated reference price effects, starting with a linear symmetric RPE (sticker shock), then a linear non-symmetric RPE (loss aversion), and finally a non-linear non-symmetric RPE (loss aversion with diminishing sensitivity). I fit the models to choice-experiment data generated by the Monthly Meat Demand Monitor project at Kansas State University. Reference price parameters were statistically significant across models, the direction of the effects was generally consistent with expectations. I compared model fit based on out-of-sample performance, the results showed that models with a linear non-symmetric RPE (loss aversion) generally performed best. On average, consumers displayed loss aversion, meaning that prices above their reference price impacted utility more that prices below their reference price. Consumers were more loss averse in retail settings than food service settings. Overall, RPEs are an important driver of consumer behavior from a statistical perspective.

The magnitude of reference price effects varies by product and across marketing channels, with implications for elasticity estimates, market share predictions, and welfare analysis. In general, I find that price elasticities are larger above the reference price (losses) than below (gains). In terms of market share predictions, price increases are typically more impactful than price decreases. Furthermore, consumer surplus decreases more when prices rise than it increases when prices fall. Overall, including RPEs in economic analysis has substantial implications for results.

My results are consistent with previous research but add an application to a previously unstudied product group across market channels, while also demonstrating the implications of various modelling approaches. My results provide additional evidence for RPEs, particularly loss aversion, in line with a large body of previous research (Mazumdar et al., 2005; Neumann & Böckenholt, 2014). However, only a small number of studies compare various types of RPEs and modelling methods (Briesch et al., 1997; Hu, 2007). Moreover, few previous paper have explored the economic significance of RPEs (Greenleaf, 1995; Kopalle et al., 1996, 2012). additionally, many studies are in a brand choice context, resulting in few studies that have examined RPEs in consumer choice across products or product categories (Bell & Lattin, 2000; Erdem et al., 2001). Finally, I am unaware of any studies which analyze RPEs for meat products or that compare retail with foodservice marketing channels. Overall, this essay contributes to the literature by adding an application to protein products in both retail and food service settings, comparing results and model performance across several RPE models, and demonstrating the economic significance of the various approaches.

This additional information provides insights into protein markets and important guidance to analysts. Protein demand has been extensively studied by agricultural economists, typically using standard neoclassical assumptions. However, this essay demonstrates that RPE models perform better and impact elasticity, market share, and consumer welfare predictions in a substantial way when compared to traditional choice models. The inclusion of RPEs in demand models for research and policy evaluation will impact the resulting economic measures.

The remainder of this essay is organized as follows: the next section is a literature review, followed by a description of the theory and methods used, then I present the results of the analysis, followed by discussion of the implications, and finally I offer some concluding comments.

Literature Review

The majority of reference price research has occurred in the marketing discipline, with some additional work in psychology, economics, and agricultural economics. Most of the empirical applications began after the development of prospect theory popularized the use of reference points as a feature of choice theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991). The literature has explored reference price formation, the presence of multiple reference prices, linear and asymmetric reference price effects, consumer heterogeneity, and reference price uncertainty. Results vary by application and empirical method, but generally support the importance of reference price effects. This literature review is primarily focused on empirical applications that are closely related to the analysis in this essay. First, I identify papers that exemplify developments in the literature which relate to my work, upon which I hope to build. Second, I identify currents gaps in the literature. Finally, I discuss where this essay will contribute to the existing body of knowledge.

Some early reference price literature in marketing focused on “sticker shock” models, where the difference between actual prices and reference prices entered the model linearly. That is, the effect of surprise was assumed to be symmetric regardless of whether it was a “gain” or “loss”. One of the first of these was Winer (1986), who proposed a brand choice model with symmetric reference price effects. Two potential assumptions about reference price formation were tested. First, extrapolative expectations, where the reference price was a function of the lagged purchase price and a trend. Second, rational expectations, where reference prices were a function of the lagged purchase price, lagged market share, and a trend. Since reference prices were not observed, these structural assumptions were necessary. Using a multinomial logit framework, he fit the model to scanner panel data on brand choice in coffee. The new model outperformed a similar model without reference price effects in terms of both in-sample fit and out-of-sample forecasting. The reference price effect was positive and significant for all brands, indicating gains (losses) increase (decrease) the probability of purchase symmetrically. However, the level of sensitivity to the reference price varied across bands. Models where reference prices assumed to form under extrapolative or rational expectations both performed equally well. However, the magnitude of the reference price effect was dramatically different; with the rational expectations assumption showing dramatically larger reference price effects. In summary, this study shows that reference price framing in consumer choice is potentially an important behavioral phenomenon that deserves attention. This study also shows evidence that reference price effects may vary across choice alternatives. Finally, the results suggest that structural assumptions about reference price formation impact the estimated reference price effects. Overall, this study is a representative example of research on RPEs using sticker shock models with symmetric effects.

Mayhew & Winer (1992) used a model with non-symmetric reference price effects to study consumer brand choice for yogurt. They used both internal and external reference prices in the model. Internal reference prices are memory based and external reference prices are stimulus based. This study used the previous period price for the internal reference price and the “regular” price displayed to the consumer before sales or discounts. Their model used common coefficients across brands for gains and losses using internal reference prices. By definition, the external reference prices are always greater than, or equal to, the purchase. Therefore, the external reference price effect enters the utility function only for gains. Price was included separately from the reference price effects. Their results show that internal and external reference prices impact the probability of choice. Furthermore, losses had a larger impact than gains, a result consistent with loss aversion. In summary, this study demonstrates the potential for multiple reference prices and provides evidence for loss aversion in consumer choice.

Hardie et al. (1993) examined reference price effects and loss aversion in consumer choice for orange juice. Their model tested for reference effects and loss aversion in both price and quality measures. Further they hypothesized a common reference point across brands and a single coefficient measuring loss aversion. Additionally, they did not include prices separately from gains and losses. Results from this study showed that incorporating reference price effects improved model fit and prediction accuracy. Results were also consistent with loss aversion, as losses impacted the probability of choice more than gains. However, loss aversion in the quality space was larger than in the price domain. Like other studies, this research uses assumptions to calculate consumer reference points which were unobserved. However, they tested several assumptions regarding reference price formation and found the current price of the brand last purchased to be the reference point that performed the best. In summary, this study demonstrates reference points across multiple choice criteria and provides further evidence for loss aversion in consumer choice.

Most of the early studies on loss aversion in consumer choice assumed homogeneity in consumer price sensitivity. Many studies had not even included the price of each product as a separate variable from the reference price terms. Bell & Lattin (2000) argued that homogenous consumer price sensitivity had a confounding effect on loss aversion estimates. They used a finite mixture model to show that when price sensitivity heterogeneity is accounted for, loss aversion is reduced or eliminated. Loss aversion completely disappeared in 6 of the 12 product categories, while reducing in magnitude withing the remaining categories. As a result, later studies took measures to control for this potential confounder.

One of the few papers in agricultural economics with reference price effects is Hu (2007). Using survey data on consumer demand for canola oil in the Japanese market, he estimated a set of multinomial logit models with reference price effects. The choice experiment included one product presented with various prices and attributes combinations. All three unique properties of the value function were tested in successive models. Results were consistent with prospect theory with statistically significant loss aversion and diminishing sensitivity parameters. However, the authors did not compare out-of-sample model performance. Furthermore, using survey data allows researchers to collect individual attributes about respondents, these were not included in the model as control variables. Yet this is the closest study to this essay because the authors considered loss aversion and diminishing sensitivity using choice experiment data.

A recent paper that is related to my present research is (Caputo et al., 2018), where choice experiment data was used to study the effect of exogenous changes in the reference price on consumer choice. Furthermore, they tested the effect of exogenous changes to the variability of the reference price. Their application was brand choice for milk and ketchup. Results indicated evidence for loss aversion, and that increased reference price variability decreases the probability of choice. The notion of reference price uncertainty was further expanded by (Caputo et al., 2020), where they derived a theoretical framework and an empirical model explicitly incorporating the reference price as a random variable with variance. Their empirical applications showed that the new model outperformed standard logit models and models treating reference price as certain.

Overall, reference price effects have been frequently studied, particularly in the marketing literature although a smaller number have appeared in economics and agricultural economics journals (Wang et al., 2021). Loss aversion is frequently found and considered by many as an empirical generalization. One meta-analysis found the mean loss aversion ratio (effect of loss divided by effect of gain) across many studies from several disciplines to be 1.955 (Alexander et al., 2021). However, the degree of loss aversion depends on individual and contextual factors (Mrkva et al., 2020).

Several important issues remain unresolved in the reference price literature. Here I identify a few of those relevant to this essay.

1. Some previous literature has compared model performance for a limited number of models. No previous work has systematically compared symmetric, loss averse, and diminishing sensitivity RPEs to determine which effects best explain consumer choice.
2. While several studies have tested various reference price formation hypotheses, they all typically rely on structural assumptions. The majority of research uses scanner data where such assumptions are necessary. However, studies utilizing survey data have an advantage because they can typically avoid these assumptions about reference price formation.
3. Nearly all the previous studies covered brand choice for a particular product, rather than consumer choice between products. Previous research may be missing the cross-price effects that include reference price effects for other goods.
4. There are no applications that measure reference price effects in consumer choice for meat products, which constitute a significant share of consumer food expenditure.
5. Most research is in a retail setting. Reference price effects have not been explored in a foodservice setting.

The literature also brings up several modeling considerations. One issue that is debated is whether to include a price effect separately from the reference price effect. Empirical researchers have argued that consumers evaluate options only relative to an anchor/reference point (Dholakia & Simonson, 2005), while others hold price sensitivity is a different phenomenon than sensitivity to gains/losses and thus should be considered separately (Erdem et al., 2001; Panzone, 2014). Given the concern that price sensitive consumers tend to have low reference prices and thus experience losses more often, including the price effect to control for price sensitivity separately seems like the better option (Bell & Lattin, 2000). This may be one reason that models that include gain/loss effects without an attribute main effect show higher levels of loss aversion than those with both effects (Neumann & Böckenholt, 2014)

Results of reference price studies have managerial implications for retailers of meat products in terms of profit maximization. Under some circumstances reference price effects can increase profits from promotions. In the case of monopoly, the optimal strategy may be a cyclical high-low pricing policy (Greenleaf, 1995). Under oligopoly, the same result holds, when consumers are heterogenous. But when the market consists of only loss averse buyers, constant low prices are optimal (Kopalle et al., 1996, 2012).

Methods & Data

Conceptual Framework

The basis for reference points in consumer choice comes from the psychology literature, where adaption level theory holds that people judge stimuli relative to a level to which they have become adapted (Helson, 1964). This concept was soon adapted by marketing researchers to the study of consumer behavior and the role of pricing in consumption decisions (Monroe, 1973). However, it was prospect theory that synthesized these concepts into a comprehensive theory of choice (Kahneman & Tversky, 1979, 1984). The analysis of reference dependent choice in riskless settings relies on the prospect theory value function—essentially a utility function—with three distinctive properties (Tversky & Kahneman, 1991). (1) Reference dependence: changes in value (utility/disutility) are derived from relative deviations from a reference level (gain/loss) rather than an absolute level. (2) Loss aversion: marginal utility is greater in absolute value below (loss) the reference point than above (gain) it. In practice this means that *the disutility of a loss is larger in magnitude than the utility of an equivalent gain.* As it is commonly put, “losses loom larger than gains”. (3) Diminishing sensitivity: diminishing marginal value (utility) in gains and losses. These three distinguishing features were first applied in the analysis of decisions under uncertainty (Kahneman & Tversky, 1979). However, the prospect theory value function provides a valuable framework for choice in riskless settings as well. One early paper applying prospect theory to consumer choice incorporated reference price effects using the concept of “transaction utility”. That is, the consumer gets utility from consumption of a good, but also derives utility/disutility from the transaction itself. The details of the transaction can enhance or attenuate the utility from consumption (Thaler, 1985). This loose conceptualization was later formalized into a theory of consumer choice (Kahneman et al., 1991; Kahneman & Tversky, 1984; Putler, 1992; Tversky & Kahneman, 1991). Since then, many empirical papers have tested for reference price effects—most often loss aversion—in consumer choice for various products and services (Neumann & Böckenholt, 2014). Much of this work was done by marketing researchers (Mazumdar et al., 2005).

Reference dependence is a necessary but not a sufficient condition for loss aversion and diminishing sensitivity. Therefore, I propose several hypotheses that progressively incorporate reference dependence, loss aversion, and diminishing sensitivity. For each hypothesis I provide a figure to illustrate a generic utility function that conforms to each hypothesis.

First, the null hypothesis:

> *Consumers of meat products evaluate prices in their absolute value; utility is a function of prices and may be linear or concave.*

The null hypothesis is the underlying assumption typically made in choice analysis when price is considered. The important point is that this assumption precludes all RPEs because consumers are assumed to evaluate prices in an absolute sense. Figure 1.1 illustrates a generic linear utility function with price as the dependent variable. An important feature of a linear function is that marginal utility is constant. Figure 1.2 illustrates a generic utility function featuring curvature with price as the dependent variable. In the figure, utility is shown to be concave, illustrating diminishing marginal utility for the combination of all other goods. However, in practice I allowed curvature to be flexible, rather than imposing concavity. Considering the possibility of curvature in my evaluation of choice is important because it serves as an alternative explanation for asymmetries that are hypothesized later in this section.

Figure 1.1: Linear utility function without reference price effects

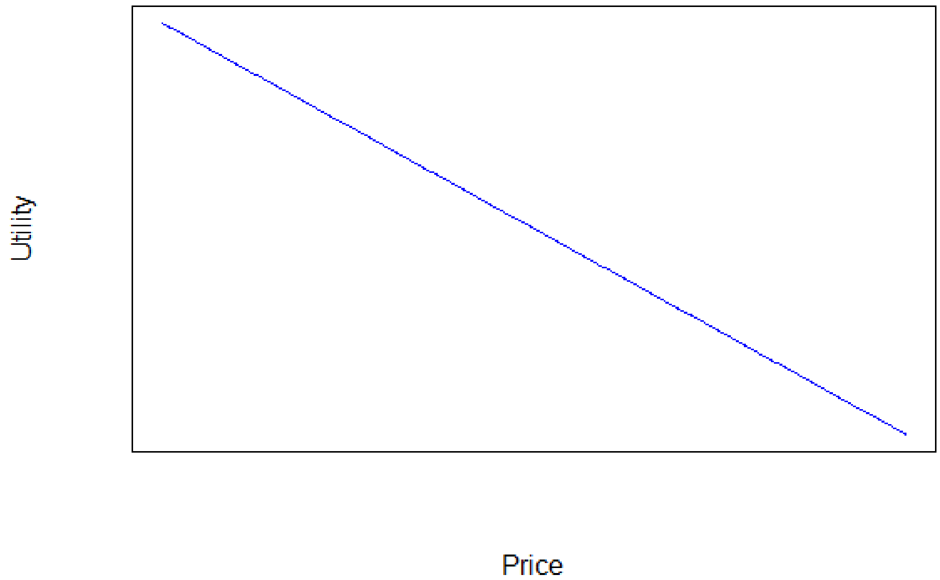
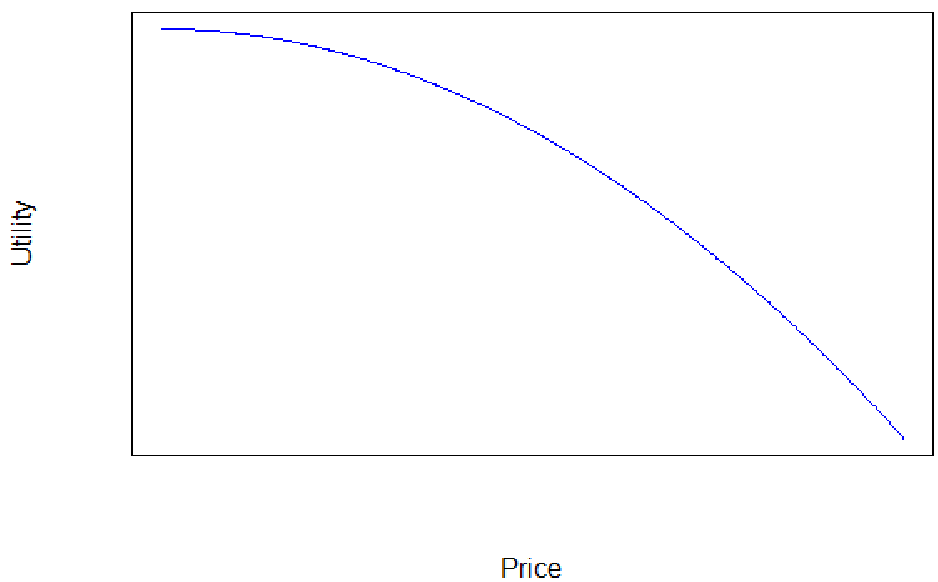


Figure 1.2: Concave utility function without reference price effects



Second, a reference dependence hypothesis:

> *In addition to the absolute price of a good, consumers of meat products evaluate prices relative to a reference price. Consumers experience a loss (gain) if the price is higher (lower) than the reference price. Marginal utility for reference price effects is constant, negative (positive) in losses (gains), and symmetric across the reference price.*

Reference dependence simply implies that consumers include an anchor price in their evaluation of the product. This hypothesis restricts the RPEs to be symmetric about the preference price; this assumption will be relaxed in subsequent hypotheses. Figure 1.3 demonstrates reference dependent utility as a function of price, where the vertical dashed line represents the reference price. A visual illustration does not clearly show the difference between linear utility and reference dependent linear utility because the RPE acts to rotate the utility function about the reference price if the own price effect is held constant. However, in practice the utility function may not rotate because the slope would simply be decomposed into a price effect and an RPE.

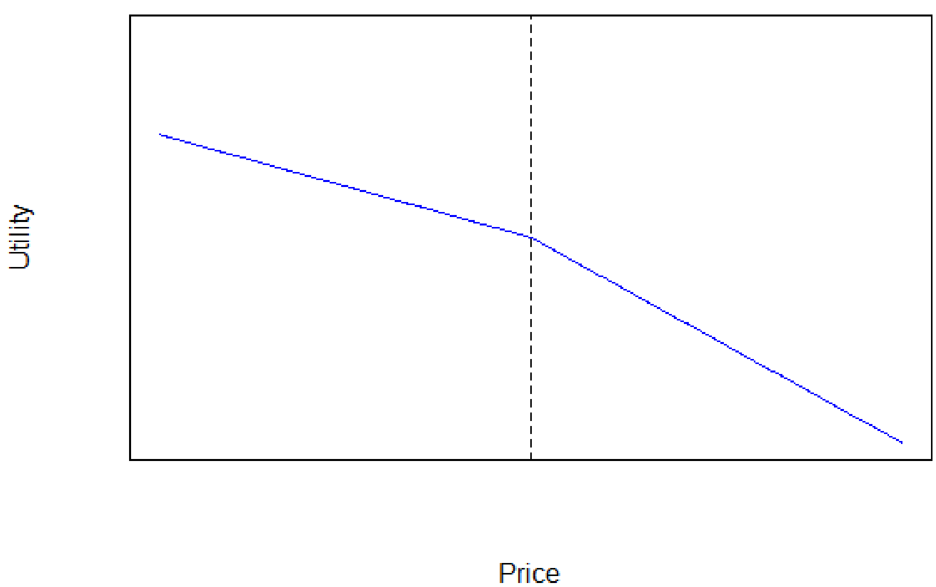
Figure 1.3: Linear and symmetric reference price effects (reference dependence)

Third, a loss aversion hypothesis:

> *In addition to the absolute price of a good, consumers of meat products evaluate prices relative to a reference price. Consumers experience a loss (gain) if the price is higher (lower) than the reference price. Marginal utility for reference price effects is constant and negative (positive) in losses (gains). Consumers are more sensitive to price losses than gains, implying the marginal utility of losses in larger than gains in absolute value.*

Loss aversion manifests itself with a kinked utility function with a steeper slope above the reference price, as shown in figure 1.4. This would lead to greater price sensitivity above the reference price potentially altering individual purchasing behavior. This would have implications for predicting product market shares and consumer welfare. However, an alternative explanation is that the utility function is simply concave, thus marginal utility changes in price. This essay will test the relative merits of a kinked vs concave utility function using stated choice data.

Figure 1.4: Linear non-symmetric reference price effects (loss aversion)

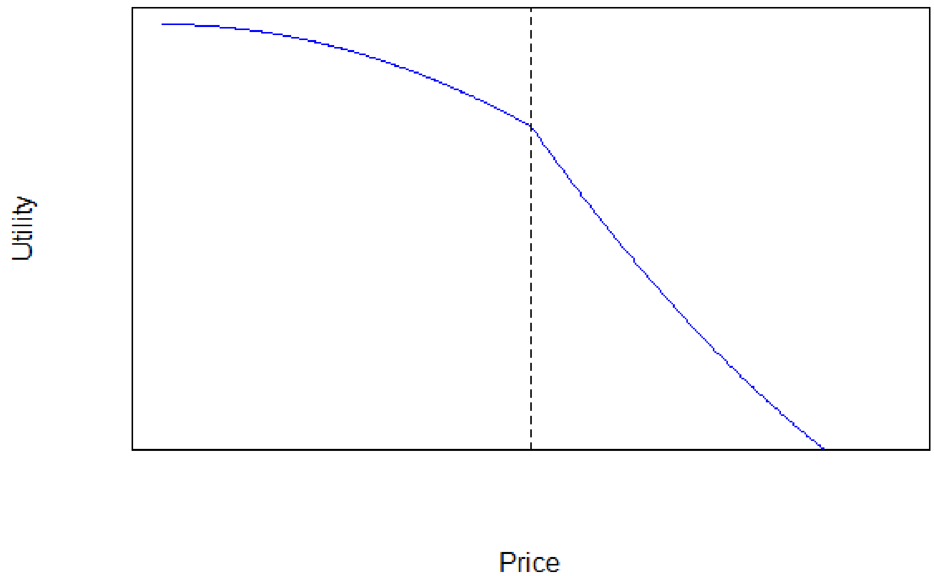


Fourth, a diminishing sensitivity hypothesis:

> *In addition to the absolute price of a good, consumers of meat products evaluate prices relative to a reference price. Consumers experience a loss (gain) if the price is higher (lower) than the reference price. Marginal utility for reference price effects is convex (concave) and negative (positive) in losses (gains). Consumers are more sensitive to price losses than gains, implying the marginal utility of losses in larger than gains in absolute value.*

This hypothesis adds diminishing sensitivity as a feature of a loss averse utility function; such that the impact on utility declines with the size of the loss or gain. This utility function is illustrated in figure 1.5. This hypothesis incorporates all of the distinctive features of the prospect theory value function into a model of consumer choice (Kahneman et al., 1991; Tversky & Kahneman, 1991).

Figure 1.5: Non-linear and non-symmetric reference price effect (loss aversion with diminishing sensitivity)



In summary, I propose a null hypothesis and three alternative hypotheses that incorporate various forms of RPEs: reference dependence, loss aversion, and diminishing sensitivity. These alternative hypotheses are grounded in an extension of prospect theory for riskless settings. The objective of this essay is to determine which hypothesis best explains consumer choice for protein and to explore the implications.

Empirical Framework

My analysis is based on the random utility random utility framework for discrete choice (McFadden, 1973). I begin with indirect utility in equation 1. An individual's indirect utility, $\boldsymbol{U_{ijt}}$, is comprised of a deterministic component, $\boldsymbol{V_{ijt}}$, and a random error $\boldsymbol{\varepsilon_{itj}}$. Each component is a vector over a choice set of J alternatives which consumer i faces at time t.

$$\boldsymbol{U_{ijt}} = \boldsymbol{V_{ijt}} + \boldsymbol{\varepsilon_{itj}} \tag{1}$$

An individual will choose option *j* at time *t*, out of choice set J, if the condition in equation 2 is met. That is, option *j* will be chosen if utility from option *j* is greater than the utility from option k for all k in J.

$$u_{ijt} > u_{ikt} \; \forall \; k \; in \; J \tag{2}$$

Because utility is stochastic, the choice is framed as the probability that utility from option *j* is greater than the utility from option k for all k in J, as shown in equation 3.

$$Prob(u_{itj} > u_{itk}) \; \forall \; k \; in \; J \tag{3}$$

However, substituting gives equation 1 into equation 3, gives us equation 4.

$$Prob(v_{ijt} + \varepsilon_{ijt} > v_{ikt} + \varepsilon_{ikt}) \; \forall \; k \; in \; J \tag{4}$$

Furthermore, if ε_{ijt} is iid and distributed according to a Type I extreme value distribution with scale parameter = 1, then the probability of selecting option *j* at time *t* is s_{ijt} as defined in equation 5.

$$s_{ijt} = \frac{exp(v_{ijt})}{\sum_{k=1}^{J} exp(v_{ikt})} \tag{5}$$

Equation 5 is the multinomial logit (conditional logit) probability of choice. The deterministic component of indirect utility, v_{ijt}, may be specified in several different ways. First, equation 6 defines a typical linear model which includes an alternative specific constant and is linear in prices.

$$v_{ijt} = \alpha_j + \gamma_j p_{ijt} \tag{6}$$

Similarly, equation 7 defines a utility function with curvature which includes an alternative specific constant and is quadratic in prices.

$$v_{ijt} = \alpha_j + \gamma_j p_{ijt} + \gamma_2 p_{ijt}^2 \tag{7a}$$

$$v_{ijt} = \alpha_j + \gamma_j p_{ijt} + \gamma_{2j} p_{ijt}^2 \tag{7b}$$

Equation 8 defines a utility function with linear symmetric reference price effects and includes an alternative specific constant and is linear in prices. I consider two variations of this utility function, one with an alternative specific reference price effect, δ_j, and another with a common parameter, δ.

$$v_{ijt} = \alpha_j + \gamma_j p_j + \delta\left(p_{ijt}^{ref} - p_{ijt}\right) \tag{8a}$$

$$v_{ijt} = \alpha_j + \gamma_j p_j + \delta_j\left(p_{ijt}^{ref} - p_{ijt}\right) \tag{8b}$$

Equation 9 defines a utility function with linear non-symmetric reference price effects and includes an alternative specific constant and is linear in prices. I consider two variations of this utility function, one with common gain and loss parameters, β and λ, and another with alternative specific reference price effects, β_j and λ_j.

$$v_{ijt} = \alpha_j + \gamma_j p_j + \beta\left(gain_{ijt} + \lambda loss_{ijt}\right) \tag{9a}$$

$$v_{ijt} = \alpha_j + \gamma_j p_j + \beta_j\left(gain_{ijt} + \lambda_j loss_{ijt}\right) \tag{9b}$$

Where, the variables $gain_{ijt}$ and $loss_{ijt}$ are defined in equation 9c and 9d. The indicator variable for gains, I_{ijt}^{gain}, is 1 if $p_{ijt}^{ref} > p_{ijt}$, and 0 otherwise. The indicator variable for losses, I_{ijt}^{loss}, is 1 if $p_{ijt}^{ref} < p_{ijt}$, and 0 otherwise.

$$gain_{ijt} = I_{ijt}^{gain}\left(p_{ijt}^{ref} - p_{ijt}\right) \tag{9c}$$

$$loss_{ijt} = I_{ijt}^{loss}\left(p_{ijt} - p_{ijt}^{ref}\right) \tag{9d}$$

Equation 10 defines a utility function with non-linear[2] and non-symmetric reference price effects and includes an alternative specific constant and is linear in prices. I consider two variations of this utility function, one with common gain and loss parameters, β and λ, and another with alternative specific reference price effects, β_j and λ_j.

$$v_{ijt} = \alpha_j + \gamma_j p_j + \beta\left[\ln\left(gain_{ijt}\right) + \lambda \ln\left(loss_{ijt}\right)\right] \tag{10a}$$

$$v_{ijt} = \alpha_j + \gamma_j p_j + \beta_j\left[\ln\left(gain_{ijt}\right) + \lambda_j \ln\left(loss_{ijt}\right)\right] \tag{10b}$$

Where, the variables $gain_{ijt}$ and $loss_{ijt}$ are defined in the same as before.

Since the RPE coefficients (δ, β, λ) measure marginal utility, interpretation is limited to relative magnitude between parameters and its sign. The exception to this is the case of the loss aversion ratio (λ), which is the ratio of marginal utility for losses to the marginal utility of gains.

[2] To operationalize the use of logarithms, one (1) was added to losses and gains to avoid undefined numbers.

Therefore, $|\lambda|=1$ implies no loss aversion. On the other hand, $|\lambda|>1$ implies loss aversion, while $|\lambda|<1$ implies gain seeking. Overall, the δ and β parameters are expected to be positive while λ parameters are expected to be negative.

For each specification the model was estimated with control variables. The addition of control variables to each model will change the model by making the intercepts and price coefficients functions of individual consumer characteristics, as shown in equation 11a for intercepts and 11b for price coefficients.

$$\alpha_j = \boldsymbol{Z_{it}\Omega_j} \tag{11a}$$

$$\gamma_j = \boldsymbol{Z_{it}\Omega} \tag{11b}$$

Where, $\boldsymbol{Z_{it}}$ is a vector of individual characteristics and $\boldsymbol{\Omega_j}$ is a vector of alternative specific coefficients, while $\boldsymbol{\Omega}$ is a vector of coefficients that are common across alternatives. Defining γ_j as a function of individual attributes helps control for the confounding effect of heterogeneity in price sensitivity (Bell & Lattin, 2000).

After models were estimated, they were ranked based on out-of-sample performance. The out of sample log likelihood function (OSLLF) approach takes the highest LL function value using the out-of-sample data as the best fitting model (Norwood et al., 2004). Additionally, the OSLLF value was exponentiated to obtain the out-of-sample likelihood value (OSLF). I use 5 iterations with 20% of the data used for fitting and 80% used for validation. Using the OSLF criterion, I rank the models from equations 6 through 10. From this exercise I select a preferred model.

The implications of model selection were demonstrated by differences in elasticities, market share predictions, and consumer welfare calculations. Elasticities were calculated above and below the reference price. I used the mean reference prices as a base, then 1% increases and decreases for the new prices. Equation 12 shows the mid-point elasticity formula that was used.

$$\eta_j = \frac{\frac{P_j^1 - P_j^0}{\left(P_j^1 + P_j^0\right)/2}}{\frac{s_j^1 - s_j^0}{\left(s_j^1 + s_j^0\right)/2}} \tag{12}$$

Where, P_j^1 and P_j^0 are the new and old prices for product j, respectively. Additionally, s_j^1 and s_j^0 are the new and old predicted choice probabilities for product j, using the new and old prices. These are calculated using the same formula as market share predictions below.

Market share predictions were made for at the mean reference price and after a hypothetical 10% price shock to chicken. The predictions were made for both a price increase and a decrease to illustrate the impact of asymmetric RPEs. The shares were calculated as shown in equation 13.

$$s_j = \frac{exp\left(v_j\right)}{\sum_{k=1}^{J} exp(v_k)} \tag{13}$$

Where, s_j is the market share for product j, v_j is the utility for product j, while v_k is the utility for an alternative product k.

Consumer surplus changes were calculated for the same $\pm$10% price change for chicken. The estimates were calculated by adapting the procedure used by Lusk et al. (2006); the formula used is shown in equation 14.

$$\Delta CS = \frac{1}{\sum_{j=1}^{J} \omega_j \left|\gamma_j\right|} \left[\ln\left(1 + \sum_{j=1}^{J} exp\left(v_j^1\right)\right) - \ln\left(1 + \sum_{j=1}^{J} exp\left(v_j^0\right)\right)\right] \tag{14}$$

Where, $\sum_{j=1}^{J} \omega_j \gamma_j$ is a weighted average of the price coefficients for all products in the choice set; interpreted as the marginal utility of income[3]. Each price parameter, γ_j, is weighted by the observed choice share, ω_j. Additionally, v_j^0 is the utility for option j, evaluated at the mean reference prices in the data. Similarly, v_j^1 is the utility for option j, evaluated after the hypothetical price change. In practice, equation 14 describes the welfare impact on an individual consumer for every choice occasion. The results are then scaled by 124,010,992 US households and 52 weeks per year, to arrive at an estimated national annual impact (US Census Bureau, 2021).

Models were estimated in R using Apollo choice modeling software (Hess & Palma, 2019). The models were fit via maximum likelihood, using the "BFGS" convergence algorithm (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; Shanno, 1970).

Data Description

To test the hypotheses of this essay I used data from the Meat Demand Monitor (MDM) project at Kansas State University (Tonsor, 2020). The data is collected between January 2020 and December 2022 via an online survey, focusing on US consumers with separate consideration of retail and food service marketing channels. The main feature of the survey as it relates to this essay is a choice experiment over various meat and alternative protein products using price as the only varying attribute. Each month, more than 2,000 US residents are surveyed, with

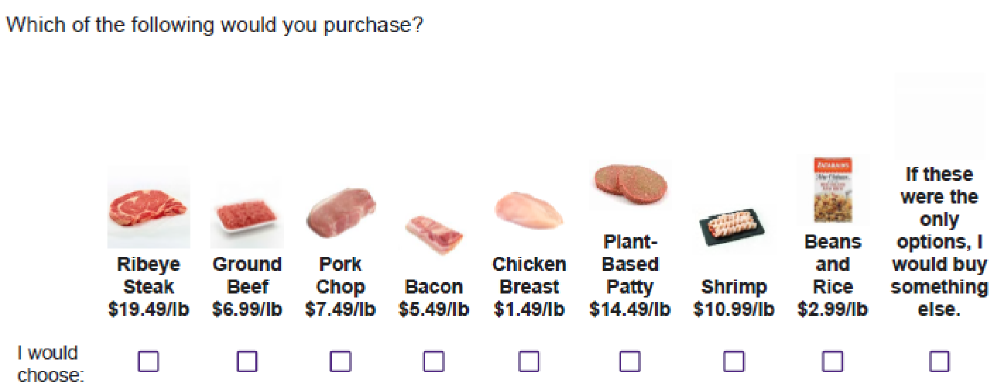
[3] There are other potential methods to approximate the marginal utility of income. Typically the price coefficient is used, thus we used a weighted average of price coefficients across product categories. However, it is unclear whether reference price effects should be included in the marginal utility of income along with the own-price effects. Only the own price coefficients were used in this analysis because they are directly tied to the consumer's utility from consumption, whereas reference price effects are tied to the circumstances of the transaction.

approximately half randomly assigned to receive questions relating to retail meat purchases and the other half receiving questions relating to food service consumption. The survey is designed to be nationally representative of the US population by age, education, gender, geographic region, household income, and race-ethnicity. However, the responses are not always fully representative. Accordingly, all estimation and analysis for this essay used weights to bring the data to a nationally representative sample (Ruggles et al., 2022).

Those respondents who were selected for retail questions participated in a choice experiment with questions like figure 1.6. Each respondent answered nine of these questions with varying prices. The instructions prior to the choice experiment were:

> *Imagine you are at the grocery store buying the ingredients to prepare a meal for you or your household. Each product would be boneless and uncooked for you to prepare at home as desired. For each of the following 9 questions, please indicate which you would most likely buy. The only difference across these 9 questions is the price ($/lb) of each option.*

Figure 1.6: Retail Choice Experiment Example Question



Every time respondents in the retail group were asked a choice experiment question, the following products were offered: ribeye steak, ground beef, pork chop, bacon, chicken breast, plant-based patty, shrimp, beans and rice, and none of these. The only attribute presented for each product was the price, which was drawn from one of three levels. The low, intermediate, and high price levels for each purchase option are shown in table 1.1.

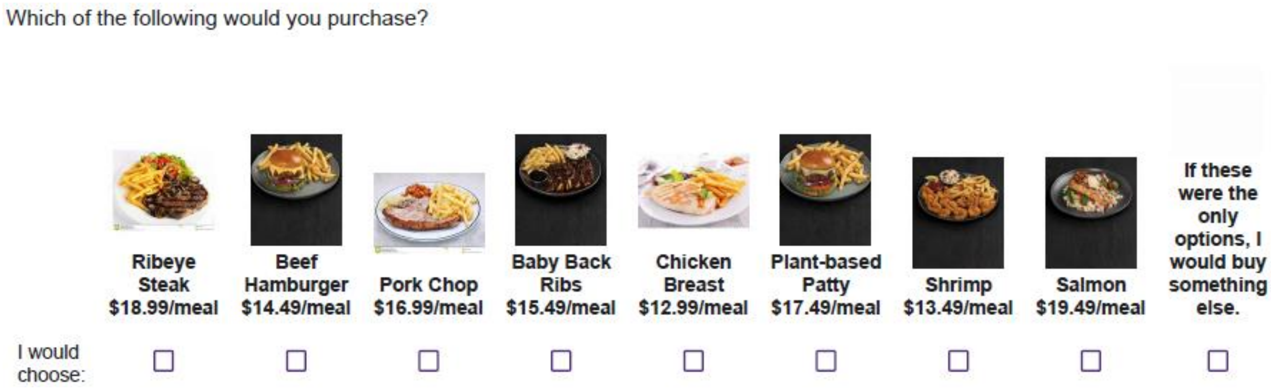
Table 1.1: Price levels for Retail Choice Experiment

Product	Low	Intermediate	High
Ribeye Steak	*$14.49*	*$16.99*	*$19.49*
Ground Beef	*$1.99*	*$4.49*	*$6.99*
Pork Chop	*$2.49*	*$4.99*	*$7.49*
Bacon	*$2.99*	*$5.49*	*$7.99*
Chicken Breast	*$1.49*	*$3.99*	*$6.49*
Plant-Based Patty	*$9.49*	*$11.99*	*$14.49*
Shrimp	*$8.49*	*$10.99*	*$13.49*
Beans and Rice	*$0.49*	*$2.99*	*$5.49*

Those respondents who were selected for food service questions participated in a choice experiment with questions like figure 1.7. Each respondent answered nine of these questions with varying prices. The instructions prior to the choice experiment were:

> *Imagine you are at your local restaurant for dinner. For each of the following 9 questions, please indicate which main entrée you would most likely select for your meal. Each product would be the dinner meal's main entrée, would be prepared as you desire, and served with two side dishes of your choosing. The only difference across these 9 questions is the meal price associated with each main entrée option.*

Figure 1.7: Food Service Choice Experiment Example Question



Every time the respondent in the food service group was asked a question, the following products were offered: ribeye steak, beef hamburger, pork chop, baby back ribs, chicken breast, plant-based patty, shrimp, salmon, and none of these. The only attribute presented for each product was the price, which was drawn from one of three levels. The low, intermediate, and high price levels for each purchase option are shown in table 1.2.

Table 1.2: Price levels for Food Service Choice Experiment

Product	Low	Intermediate	High
Ribeye Steak	*$18.99*	*$21.49*	*$23.99*
Hamburger	*$9.49*	*$11.99*	*$14.49*
Pork Chop	*$14.49*	*$16.99*	*$19.49*
Baby Back Ribs	*$12.99*	*$15.49*	*$17.99*
Chicken Breast	*$10.49*	*$12.99*	*$15.49*
Plant-Based Patty	*$12.49*	*$14.99*	*$17.49*
Shrimp	*$10.99*	*$13.49*	*$15.99*
Salmon	*$14.49*	*$16.99*	*$19.49*

For both the retail and the food service choice experiments, the prices appearing in each choice were determined by a main effects orthogonal fractional factorial design. This means that prices of each alternative were uncorrelated with the other alternatives. The choice experiment design required 27 choices for full orthogonality. Rather than present 27 choices to each respondent, the choices were blocked into three sets of nine, each respondent in the retail group was randomly assigned to one of the three blocks. Therefore, each respondent made nine choices with randomly drawn prices for each of the nine products. Table 1.3 shows the product shares from the data.

Table 1.3: Unweighted Product Shares

Product	Number Chosen	Percent Chosen
	Retail (N=367,812)	
Ribeye Steak	*26,654*	*7.25%*
Ground Beef	*81,965*	*22.28%*
Pork Chop	*50,066*	*13.61%*
Bacon	*29,783*	*8.10%*
Chicken Breast	*93,063*	*25.30%*
Plant-based Patty	*10,600*	*2.88%*
Shrimp	*17,795*	*4.84%*
Beans & Rice	*29,186*	*7.94%*
None of These	*28,700*	*7.80%*
	Food Service (N=368,721)	
Ribeye Steak	*51,034*	*13.84%*
Hamburger	*80,760*	*21.90%*
Pork Chop	*15,948*	*4.33%*
Baby Back Ribs	*39,103*	*10.61%*
Chicken Breast	*53,982*	*14.64%*
Plant-based Patty	*16,821*	*4.56%*
Shrimp	*53,581*	*14.53%*
Salmon	*32,388*	*8.78%*
None of These	*25,104*	*6.81%*

Before respondents participated in the choice experiment, each was asked about their price expectations for each of the products in the choice set. The question gave respondents a discrete choice in which they chose one of five pre-defined price intervals for each product. These intervals are shown in table 1.4 for the retail choice experiment and table 1.5 for the food service choice experiment. The mid-point between bounds was used as the respondent’s reference price in the analysis. This reference price would be considered an internal reference point because it is memory based, which tend produce smaller loss aversion estimates (van Oest, 2013). Perhaps this is a result of greater reference price uncertainty when consumers rely on their own memory than when an external—stimulus based—reference price (e.g. manufacturer's suggested retail price) is used (Caputo et al., 2020). Additionally, the reference price question in the survey gives the respondent context and is asked immediately prior to the choice experiment; allowing the reference price to be dynamic and context specific (Baucells et al., 2011). The reference price question for respondents in the retail group was worded as follows:

> *Please indicate the price ($/lb) you would expect a grocery store in your area to charge for the following products. Each product would be boneless and uncooked for you to prepare at home as desired.*

Table 1.4: Reference Price Intervals for Respondents Assigned to Retail CE

Product	Option 1	Option 2	Option 3	Option 4	Option 5
Ribeye Steak	*<$15.50*	*$15.50-$16.49*	*$16.50-$17.49*	*$17.50-$18.49*	*$18.50 +*
Ground Beef	*<$2.99*	*$3.00-$3.99*	*$4.00-$4.99*	*$5.00-$5.99*	*$6.00 +*
Pork Chop	*<$3.50*	*$3.50-$4.49*	*$4.50-$5.49*	*$5.50-$6.49*	*$6.50 +*
Bacon	*<$4.00*	*$4.00-$4.99*	*$5.00-$5.99*	*$6.00-$6.99*	*$7.00 +*
Chicken Breast	*<$2.50*	*$2.50-$3.49*	*$3.50-$4.49*	*$4.50-$5.49*	*$5.50 +*
Plant Based Patty	*<$10.50*	*$10.50-$11.49*	*$11.50-$12.49*	*$12.50-$13.49*	*$13.50 +*
Shrimp	*<$9.50*	*$9.50-$10.49*	*$10.50-$11.49*	*$11.50-$12.49*	*$12.50 +*
Beans & Rice	*<$1.50*	*$1.50-$2.49*	*$2.50-$3.49*	*$3.50-$4.49*	*$4.50 +*

The reference price question for respondents in the retail group was worded as follows:

> *Please indicate the price ($/meal) you would expect a restaurant in your area to charge for dinner meals including the following products. Each product would be the dinner meal's main entrée, would be prepared as you desire, and served with two side dishes of your choosing.*

Table 1.5: Reference Price Intervals for Respondents Assigned to Food Service CE

Product	Option 1	Option 2	Option 3	Option 4	Option 5
Ribeye Steak	< *$20.00*	*$20.00-$20.99*	*$21.00-$21.99*	*$22.00-$22.99*	*$23.00 +*
Hamburger	< *$10.50*	*$10.50-$11.49*	*$11.50-$12.49*	*$12.50-$13.49*	*$13.50 +*
Pork Chop	< *$15.50*	*$15.50-$16.49*	*$16.50-$17.49*	*$17.50-$18.49*	*$18.50 +*
Baby Back Ribs	< *$14.00*	*$14.00-$14.99*	*$15.00-$15.99*	*$16.00-$16.99*	*$17.00 +*
Chicken Breast	< *$11.50*	*$11.50-$12.49*	*$12.50-$13.49*	*$13.50-$14.49*	*$14.50 +*
Plant Based Patty	< *$13.50*	*$13.50-$14.49*	*$14.50-$15.49*	*$15.50-$16.4*	*$16.50 +*
Shrimp	< *12.00*	*$12.00-$12.99*	*$13.00-$13.99*	*$14.00-$14.99*	*$15.00 +*
Salmon	< *$15.50*	*$15.50-$16.49*	*$16.50-$17.49*	*$17.50-$18.49*	*$18.50 +*

The survey question did not include a lower bound for option 1, nor did it include an upper bound for option 5. For this essay, 0 was used as the lower bound of the interval for option 1. For option 5, the upper bound was calculated by adding the upper bound from option 1 to the lower bound for option 5. This results in option 1 and 5 being symmetric in terms of the distance between bounds.

The reference price for each product was used to calculate the corresponding gains and losses within each choice scenario the respondent faced, using the formula in equation 9. For successful estimation, it was important to determine that the data contained enough observed gains and losses for each product. Tables 1.6 and 1.7 give summary statistics for reference prices, gains, and losses for each product in both the retail and food service datasets. Note that the minimum and maximum are dictated by the survey design itself.

Table 1.6: Reference Price Summary for Retail

Variable Name	Product	Observations	Proportion	Mean	SD	Min	Max
Reference Price	Ribeye Steak	*367,812*		*13.95*	*5.76*	*7.75*	*26.25*
	Ground Beef	*367,812*		*4.16*	*1.68*	*1.50*	*7.50*
	Pork Chop	*367,812*		*4.27*	*1.88*	*1.75*	*8.25*
	Bacon	*367,812*		*4.55*	*1.99*	*2.00*	*9.00*
	Chicken Breast	*367,812*		*3.58*	*1.66*	*1.25*	*6.75*
	Plant Based Patty	*367,812*		*7.93*	*3.69*	*5.25*	*18.75*
	Shrimp	*367,812*		*9.53*	*3.82*	*4.75*	*17.25*
	Beans & Rice	*367,812*		*2.00*	*1.18*	*0.75*	*5.25*
Loss	Ribeye Steak	*247,501*	*67.3%*	*6.54*	*3.92*	*0.99*	*11.75*
	Ground Beef	*198,939*	*54.1%*	*2.52*	*1.48*	*0.50*	*5.50*
	Pork Chop	*216,132*	*58.8%*	*2.68*	*1.64*	*0.75*	*5.75*
	Bacon	*225,977*	*61.4%*	*2.84*	*1.71*	*1.00*	*6.00*
	Chicken Breast	*205,049*	*55.7%*	*2.43*	*1.49*	*0.25*	*5.25*
	Plant Based Patty	*290,033*	*78.9%*	*5.72*	*2.63*	*1.00*	*9.25*
	Shrimp	*220,405*	*59.9%*	*4.32*	*2.61*	*1.00*	*8.75*
	Beans & Rice	*215,371*	*58.6%*	*2.56*	*1.33*	*0.25*	*4.75*
Gain	Ribeye Steak	*120,311*	*32.7%*	*3.59*	*3.64*	*0.01*	*11.76*
	Ground Beef	*168,873*	*45.9%*	*1.84*	*1.50*	*0.01*	*5.51*
	Pork Chop	*151,680*	*41.2%*	*1.85*	*1.52*	*0.01*	*5.76*
	Bacon	*141,835*	*38.6%*	*1.84*	*1.53*	*0.01*	*6.01*
	Chicken Breast	*162,763*	*44.3%*	*1.70*	*1.48*	*0.01*	*5.26*
	Plant Based Patty	*77,779*	*21.1%*	*2.54*	*2.35*	*0.01*	*9.26*
	Shrimp	*147,407*	*40.1%*	*2.81*	*2.49*	*0.01*	*8.76*
	Beans & Rice	*152,441*	*41.4%*	*1.24*	*1.17*	*0.01*	*4.76*

Table 1.7: Reference Price Summary for Food Service

Variable Name	Product	Observations	Proportion	Mean	SD	Min	Max
Reference Price	Ribeye Steak	*368,721*		*20.92*	*7.83*	*10.00*	*33.00*
	Hamburger	*368,721*		*8.53*	*3.76*	*5.25*	*18.75*
	Pork Chop	*368,721*		*12.54*	*5.24*	*7.75*	*26.25*
	Baby Back Ribs	*368,721*		*15.30*	*5.43*	*7.00*	*24.00*
	Chicken Breast	*368,721*		*10.10*	*4.18*	*5.75*	*20.25*
	Plant Based Patty	*368,721*		*10.20*	*4.58*	*6.75*	*23.25*
	Shrimp	*368,721*		*13.67*	*5.03*	*6.00*	*21.00*
	Salmon	*368,721*		*15.99*	*6.02*	*7.75*	*26.25*
Loss	Ribeye Steak	*194,428*	*52.7%*	*6.74*	*5.00*	*0.99*	*13.99*
	Hamburger	*283,295*	*76.8%*	*5.46*	*2.81*	*1.00*	*9.24*
	Pork Chop	*274,888*	*74.6%*	*7.03*	*3.77*	*0.99*	*11.74*
	Baby Back Ribs	*179,714*	*48.7%*	*4.92*	*3.53*	*1.00*	*10.99*
	Chicken Breast	*261,674*	*71.0%*	*5.34*	*3.07*	*1.00*	*9.74*
	Plant Based Patty	*287,234*	*77.9%*	*6.83*	*3.11*	*1.00*	*10.74*
	Shrimp	*170,265*	*46.2%*	*4.54*	*3.08*	*1.00*	*9.99*
	Salmon	*195,588*	*53.0%*	*5.64*	*3.91*	*0.99*	*11.74*
Gain	Ribeye Steak	*174,293*	*47.3%*	*5.93*	*5.09*	*0.01*	*14.01*
	Hamburger	*85,426*	*23.2%*	*2.39*	*2.29*	*0.01*	*9.26*
	Pork Chop	*93,833*	*25.4%*	*2.77*	*3.15*	*0.01*	*11.76*
	Baby Back Ribs	*189,007*	*51.3%*	*4.12*	*3.68*	*0.01*	*11.01*
	Chicken Breast	*107,047*	*29.0%*	*2.46*	*2.58*	*0.01*	*9.76*
	Plant Based Patty	*81,487*	*22.1%*	*2.81*	*2.86*	*0.01*	*10.76*
	Shrimp	*198,456*	*53.8%*	*4.24*	*3.32*	*0.01*	*10.01*
	Salmon	*173,133*	*47.0%*	*4.25*	*4.00*	*0.01*	*11.76*

Figures 1.8 and 1.9 represent the distribution of gains and losses by product for the retail and food service datasets respectively. For these figures there is a dotted line at zero on the vertical axis; observations above the line represent losses, while observations below the line represent gains. In the retail dataset, all products have at least 25% of the data in either gains or losses, except for the plant-based patty product category. However, the plant-based patty product category had 21.1% of observations as gains. In the food service dataset, all products have at least 25% of the data in either gains or losses, except for hamburger and plant-based patty

product categories. However, 22.1% and 23.2% of observations were gains for plant-based patty and hamburger, respectively.

Figure 1.8: Variation in Gains and Losses by Product for Retail Data

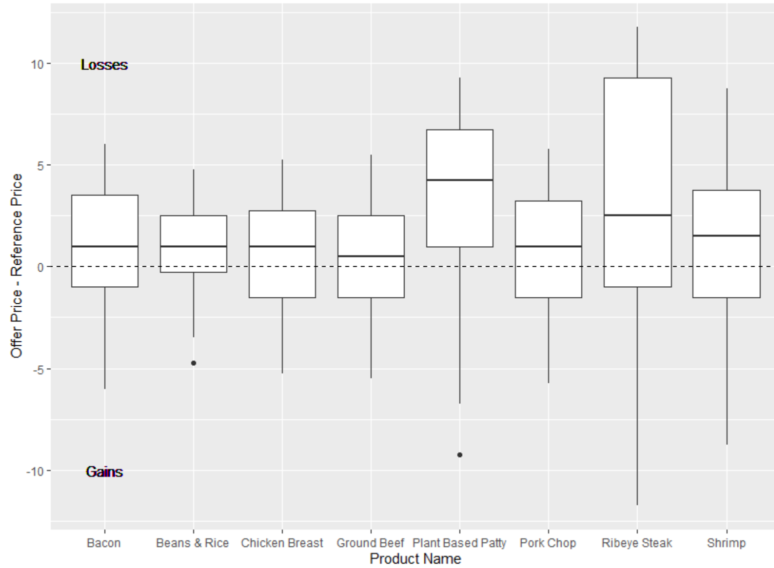
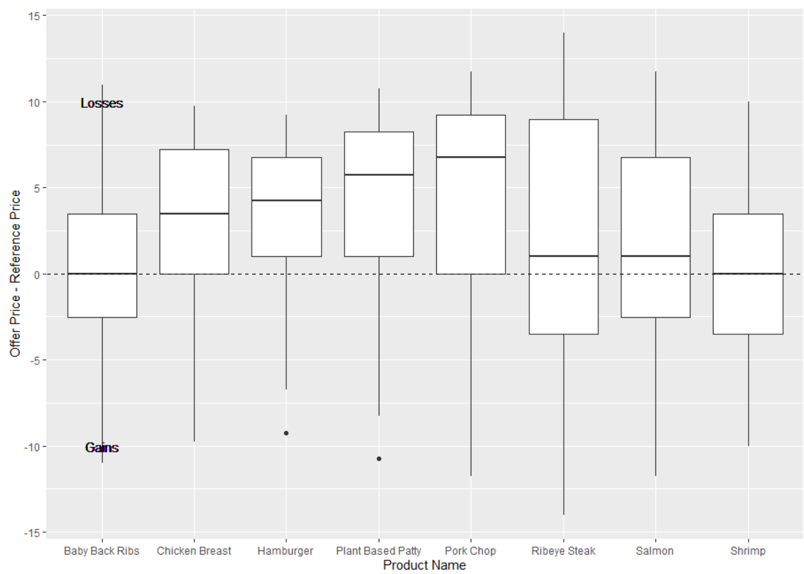


Figure 1.9: Variation in Gains and Losses by Product for Food Service Data



The nature of this data as a repeated cross section implies that there is variation over time as well as across individuals. The study period coincided with a period of general inflation in the United States. This fact is likely the driver of the upward trends observed in figures 1.10 and 1.11. This variation over time shows that reference prices are dynamic, and consumers update them based on current market conditions.

Figure 1.10: Consumer Reference Price Selections Over Time for Retail Data

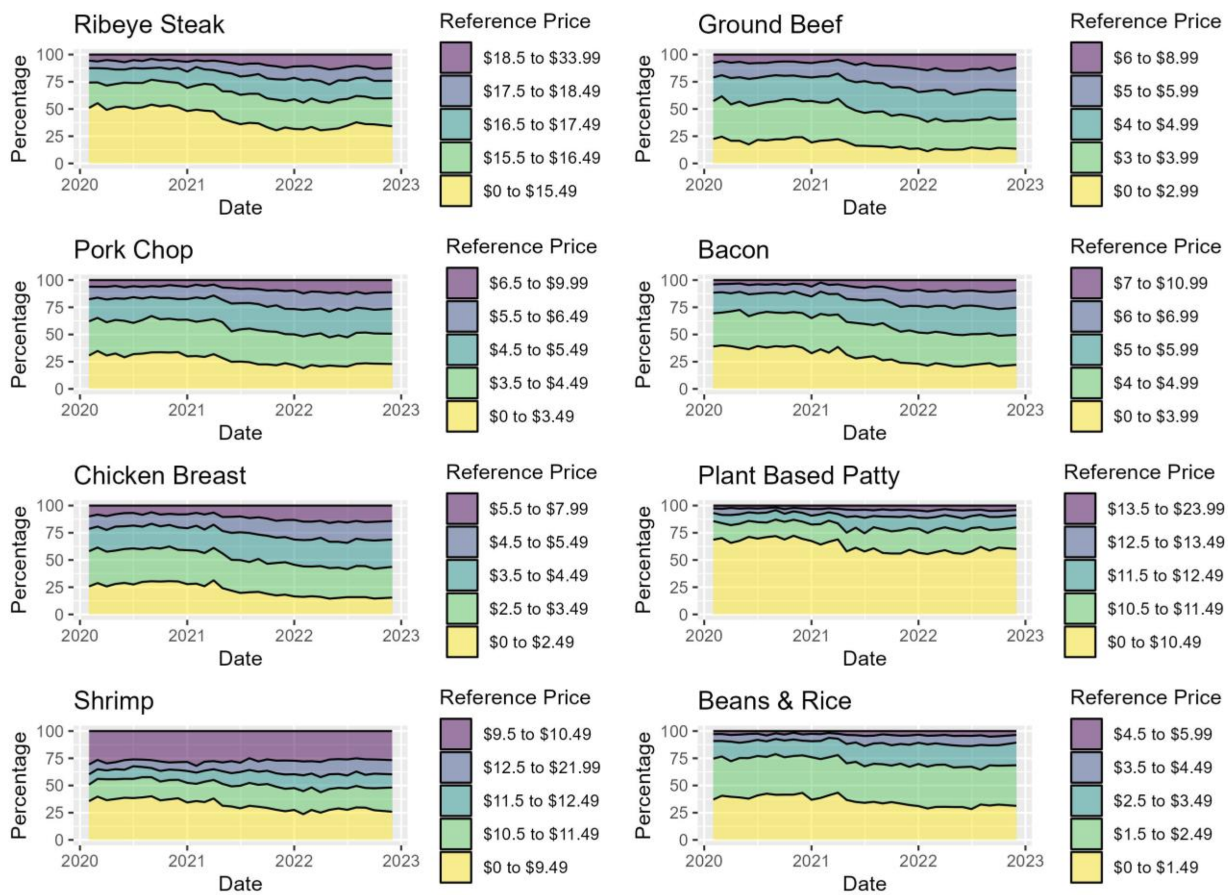
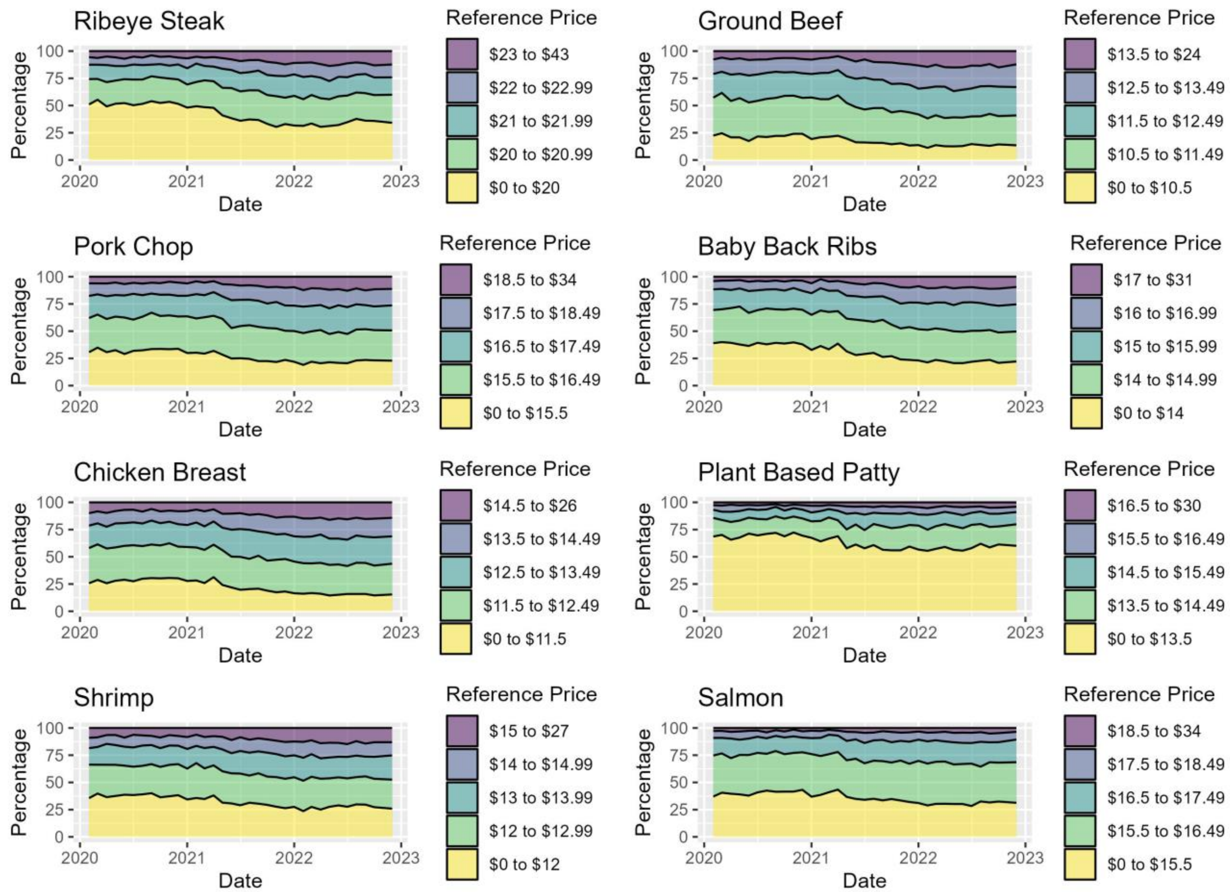


Figure 1.11: Consumer Reference Price Selections Over Time for Food Service Data



This dataset is unique among other datasets commonly used in reference price research. One distinguishing feature is the availability of many socio-economic, demographic, and other characteristics within the data. Many other studies that have been published rely on supermarket scanner data, while this data is survey based. The variables selected for inclusion in the model (see equation 11) are summarized in table 1.8. The majority of these variables are dummy variables, so a reference category is necessary for variables in a set. The selected reference categories were household income $60k - $120k, white, and Midwest census region. The remaining dummy variables are individually interpretable as yes or no. Age is the only control variable that was included as a continuous measure.

Table 1.8: Unweighted Summary for Control Variables

Variable Name	Retail (N=367,812)	Food Service (N=368,721)
Household Income < $60k	*58.3%*	*58.1%*
Household Income $60k - $120k	*30.1%*	*30.1%*
Household Income > $120k	*11.6%*	*11.9%*
White	*75.3%*	*75.8%*
Black	*13.4%*	*13.4%*
Asian	*5.7%*	*5.5%*
Other Race	*5.6%*	*5.3%*
Hispanic or Latino	*12.4%*	*12.2%*
Female	*53.5%*	*53.8%*
College Degree	*48.0%*	*48.1%*
Regular Meat Eater	*72.5%*	*72.7%*
Primary Shopper	*72.6%*	*72.3%*
Midwest Census Region	*22.0%*	*22.0%*
Northeast Census Region	*17.9%*	*17.9%*
South Census Region	*39.0%*	*38.9%*
West Census Region	*21.1%*	*21.2%*
Age	*Mean 49.8; SD 17.1; Min 18; Max 99*	*Mean 49.9; SD 17.2; Min 18; Max 99*

Overall, this dataset has several distinct advantages. First is its large size, with 367,812 observations in the retail portion and 368,721 in the food service portion. Second, the data covers food service choices; a marketing channel that has not been studied in the reference price literature. Third, this dataset has many covariates that can be used as control variables. However, the data is also from a choice experiment and could be subject to hypothetical bias[4].

Results

The primary results of this essay are the estimated model parameters and model performance metrics. Secondary results are presented later and illustrate the implications of the

[4] Every effort was made to remove observations that were likely to be biased. For example, respondent were removed from the sample if they selected the wrong answer in a color "speed check". We also filtered observations for respondents who took less than a minute on the survey, were under 18, rarely to never shopped for groceries, or did not affirm their honesty in answering the survey.

main results. The first set of results are model performance metrics, with a particular focus on out-of-sample performance. These results provide criteria for selecting the utility specification with the most appropriate functional form, based on the observed data. The second set of results are coefficient estimates for reference price effects in each of the applicable models. These provide a sense of the magnitude of the effects while also allowing statistical tests for each coefficient. Subsequently, I present the secondary results: elasticities and the impact of hypothetical price changes in terms of consumer welfare and market share adjustments. Combined, these results allow us to draw conclusions as to which models are most correct; then to determine how much model selection matters for economic predictions.

Model Performance

All models that were estimated for this essay were subjected to out-of-sample validation. These results are presented in table 1.9. Notably, both in-sample and out-of-sample measures produced the same ranking of model performance. Models are grouped by market channel within the table. Models with reference price effects always outperformed models without. However, the ranking of reference price models varies across marketing channels. For both marketing channels product specific loss aversion performed the best followed by product specific loss aversion with diminishing sensitivity. In general, reference price models with product specific parameters performed best. However, in the retail data, product specific sticker shock models performed worse than models with a common asymmetric RPE. Among models with a common RPE across products, the ordering of models varies. In retail data, best to worst order: loss aversion with diminishing sensitivity, loss aversion, and sticker shock. In food service: loss aversion, sticker shock, and loss aversion with diminishing sensitivity. Overall, the evidence indicates that RPEs improve performance in consumer choice models. Furthermore, the evidence also indicates that loss aversion is the best explanation for consumer behavior in relation to reference prices. However, diminishing sensitivity is not clearly present in every case, although it is apparently stronger in the retail setting. The difference across market channels points to potential structural heterogeneity in how consumers make purchase decisions.

Asymmetric RPE models (loss aversion) consistently outperformed quadratic models in out-of-sample measures. Indeed, quadratic models—both with product specific and common parameters—showed very little improvement in out of sample performance compared to the baseline linear model. Models with product specific quadratic price terms performed 0.35% and 0.09% better than the baseline, in retail and food service respectively. On the other hand, models featuring product specific loss aversion improved out-of-sample performance by as much as 1.53% and 2.09% for retail and food service. Together, these facts provide evidence that asymmetric RPEs are not simply driven by utility function curvature.

Generally, loss averse models performed better than sticker shock models with linear RPEs. For the retail data, models with loss aversion improved out-of-sample performance between 1.19% and 1.52%; whereas sticker shock models improved performance between 0.85% to 0.89%. When the models were fit using food service data, the results were less clear-cut. However, loss aversion still seems to describe the data better than symmetric sticker shock models. For models with a common parameter, linear loss aversion was only slightly better than the sticker shock model with improvements of 1.79% and 1.76% respectively. For models with product specific parameters, the sticker shock model improved performance 1.95% while the loss aversion model improved performance by 2.09%. In summary, asymmetric RPEs (loss aversion) fit the data better than symmetric RPEs (sticker shock).

In general, the evidence favors linear loss aversion over loss aversion with diminishing sensitivity. However, the difference in performance between these alternative models is typically small. The only instance where diminishing sensitivity improved performance was for models with a common parameter, on retail data. In every other case, linear loss aversion improved performance over the baseline between 1.19% and 2.09%. Yet, the improvement over loss aversion with diminishing sensitivity was sometimes as small as 0.05 percentage points. In sum, linear asymmetric RPEs perform better than similar models that are non-linear in gains and losses, although the difference in performance is relatively small.

Table 1.9: Model Performance

Equation	Model Features	Estimated Parameters	Adj. Rho Sq	AIC	BIC	OSLLF	OSLF	% Chg in OSLF vs BL
				Retail				
9b*	Product specific loss aversion	*155*	*0.2116*	*1,274,286*	*1,275,962*	*-1.7387*	*0.1757*	*1.53%*
10b*	Product specific loss aversion and diminishing sensitivity	*155*	*0.2115*	*1,274,514*	*1,276,190*	*-1.7393*	*0.1756*	*1.48%*
10a	Loss aversion and diminishing sensitivity	*141*	*0.2106*	*1,275,941*	*1,277,466*	*-1.7409*	*0.1754*	*1.32%*
9a	Loss aversion	*141*	*0.2101*	*1,276,730*	*1,278,255*	*-1.7421*	*0.1752*	*1.19%*
8b	Product specific sticker shock	*147*	*0.2088*	*1,278,836*	*1,280,426*	*-1.7451*	*0.1746*	*0.89%*
8a	Sticker shock	*140*	*0.2085*	*1,279,280*	*1,280,794*	*-1.7454*	*0.1746*	*0.85%*
7b	Product specific quadratic	*147*	*0.2062*	*1,283,069*	*1,284,659*	*-1.7505*	*0.1737*	*0.35%*
7a	Quadratic	*140*	*0.2047*	*1,285,501*	*1,287,015*	*-1.7537*	*0.1731*	*0.02%*
6	Baseline	*139*	*0.2046*	*1,285,662*	*1,287,166*	*-1.7539*	*0.1731*	*0.00%*
				Food Service				
9b*	Product specific loss aversion	*155*	*0.1194*	*1,426,932*	*1,428,609*	*-1.9436*	*0.1432*	*2.09%*
10b	Product specific loss aversion and diminishing sensitivity	*155*	*0.1190*	*1,427,474*	*1,429,151*	*-1.9441*	*0.1431*	*2.04%*
8b	Product specific sticker shock	*147*	*0.1186*	*1,428,178*	*1,429,769*	*-1.9450*	*0.1430*	*1.95%*
9a	Loss aversion	*141*	*0.1178*	*1,429,514*	*1,431,040*	*-1.9465*	*0.1428*	*1.79%*
8a	Sticker shock	*140*	*0.1176*	*1,429,763*	*1,431,277*	*-1.9468*	*0.1427*	*1.76%*
10a	Loss aversion and diminishing sensitivity	*141*	*0.1164*	*1,431,745*	*1,433,270*	*-1.9495*	*0.1423*	*1.48%*
7b	Product specific quadratic	*147*	*0.1100*	*1,442,023*	*1,443,613*	*-1.9633*	*0.1404*	*0.09%*
7a	Quadratic	*140*	*0.1095*	*1,442,823*	*1,444,337*	*-1.9642*	*0.1403*	*0.00%*
6	Baseline	*139*	*0.1095*	*1,442,839*	*1,444,343*	*-1.9642*	*0.1403*	*0.00%*

Note: All models in this table were estimated with the full set of controls.
* For these models, some eigenvalues of Hessian were positive. This could point to an identification or estimation problem. Potentially driven by thin data for some groups segmented by control variables.

Coefficient Estimates for Reference Price Effects

Regression coefficients for RPEs contain information on how reference prices influence consumer choice. Model coefficients for reference price effects are presented in tables 1.10 and 1.11. Across all models, most reference price coefficients were statistically significant. Additionally, most of the signs were consistent with expectations; with the exception of some product specific gain parameters (β) being negative. Furthermore, nearly all loss aversion ratios (λ) were greater than one in absolute value, showing consistent evidence for loss aversion. Overall, coefficients for RPEs show that gains typically improve utility while losses diminish it; furthermore, loss aversion is typically present when asymmetry is allowed.

Sticker shock model coefficients indicate that reference prices play a role in consumer choice. Positive and statistically significant (except beans & rice in a retail setting) coefficients indicate that gains increase utility while losses decrease it. Product specific coefficients vary across products and market channels. In food service products like hamburger and chicken breast which have high choice shares have the smallest coefficients, and yet this pattern doesn't seem to be reflected in the retail results. Although the sticker shock coefficients cannot be directly interpreted because they are in terms of utility, the direction is consistent with expectations and the statistical significance confirms the existence of RPEs.

The loss averse model coefficients indicate that consumers are more impacted by losses than gains and are therefore loss averse[5]. For these models the loss aversion parameter (λ) is the

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[5] Some lambda coefficients are positive, but they are always paired with a negative beta; this indicates diminishing utility in both losses and gains with losses having a larger impact. This occurs in a small minority of products and could indicate gains do not always improve consumer utility for some specific products.

ratio of marginal utility for losses over gains. Nearly all these ratios are statistically greater than one in absolute value. Generally, loss aversion ratios are larger in the retail setting than the food service setting. For models with a common parameter, the estimates are -6.76 for retail and -1.42 for food service. For models with product specific parameters, the estimates range from -1.16 to -144.44 in the retail setting and from -1.01 to -34.75 in the food service setting. Overall, loss aversion is evident in consumer choice for both market channels and across the majority of products.

For the loss averse model with diminishing sensitivity, coefficients also generally indicate loss aversion. Nearly all these ratios are statistically greater than one in absolute value. Generally, loss aversion ratios are larger in the retail setting than the food service setting. For models with a common parameter, the estimates are -47.71 for retail and -1.33 for food service. For models with product specific parameters, the estimates range from -1.19 to -299.80 in the retail setting and from -0.79 to -113.28 in the food service setting. The large loss aversion ratios are primarily driven by very small values for the gain parameter. This indicates that gains matter very little, while losses remain impactful. Overall, loss aversion is evident in consumer choice when diminishing sensitivity was imposed as an assumption.

Table 1.10: Coefficient Estimates for Reference Price Effects (Retail).

Equation	8a	9a	10a	8b	9b§	10b§
Model Feature	**Sticker shock**	**Loss aversion**	**Loss aversion and diminishing sensitivity**	**Product specific sticker shock**	**Product specific loss aversion**	**Product specific loss aversion and diminishing sensitivity**
Parameter	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
δ	*0.071****					
β		*0.019****	*0.009****			
λ		*-6.755†††*	*-47.707†††*			
δ_{Ribeye}				*0.074****		
$\delta_{Ground\ Beef}$				*0.061****		
$\delta_{Pork\ Chop}$				*0.043****		
δ_{Bacon}				*0.073****		
$\delta_{Chicken\ Breast}$				*0.093****		
$\delta_{Plant-Based}$				*0.051****		
δ_{Shrimp}				*0.081****		
$\delta_{Beans\ \&\ Rice}$				*0.005*		
β_{Ribeye}					*0.07****	*0.262****
$\beta_{Ground\ Beef}$					*-0.001*	*-0.001****
$\beta_{Pork\ Chop}$					*0.002****	*0.001****
β_{Bacon}					*0.06****	*0.168****
$\beta_{Chicken\ Breast}$					*0.002****	*0.002****
$\beta_{Plant-Based}$					*-0.004****	*-0.004****
β_{Shrimp}					*0.006****	*0.005****
$\beta_{Beans\ \&\ Rice}$					*-0.013****	*-0.141****
λ_{Ribeye}					*-1.159*	*-1.192*
$\lambda_{Ground\ Beef}$					*125.517*	*295.227†††*
$\lambda_{Pork\ Chop}$					*-99.467†††*	*-299.796†††*
λ_{Bacon}					*-1.864††*	*-1.364*
$\lambda_{Chicken\ Breast}$					*-144.451†††*	*-276.972†††*
$\lambda_{Plant-Based}$					*22.201†††*	*78.045†††*
λ_{Shrimp}					*-24.857†††*	*-107.779†††*
$\lambda_{Beans\ \&\ Rice}$					*9.46†††*	*1.852*

Statistical Significance:
For tests with a null of 0: (***) indicates p<0.01; (**) indicates p<0.05; (*) indicates p<0.10.
For tests with a null of |1|: (†††) indicates p<0.01; (††) indicates p<0.05; (†) indicates p<0.10.
§These models successfully converged. However, some eigenvalues of Hessian were positive. This could point to an identification or estimation problem. Potentially thin data for some groups segmented by control variables.

Table 1.11: Coefficient Estimates for Reference Price Effects (Food Service).

Equation	8a	9a	10a	8b	9b§	10b
Model Feature	**Sticker shock**	**Loss aversion**	**Loss aversion and diminishing sensitivity**	**Product specific sticker shock**	**Product specific loss aversion**	**Product specific loss aversion and diminishing sensitivity**
Parameter	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
δ	*0.051****					
β		*0.043****	*0.149****			
λ		*-1.421†††*	*-1.333†††*			
δ_{Ribeye}				*0.054****		
$\delta_{Hamburger}$				*0.028****		
$\delta_{Pork\ Chop}$				*0.057****		
$\delta_{Baby\ Back\ Ribs}$				*0.052****		
$\delta_{Chicken\ Breast}$				*0.026****		
$\delta_{Plant-Based}$				*0.035****		
δ_{Shrimp}				*0.046****		
δ_{Salmon}				*0.073****		
β_{Ribeye}					*0.055****	*0.265****
$\beta_{Hamburger}$					*0.002****	*0.003****
$\beta_{Pork\ Chop}$					*0.003**	*0.013****
$\beta_{Baby\ Back\ Ribs}$					*0.042****	*0.171****
$\beta_{Chicken\ Breast}$					*0.001****	*0.001****
$\beta_{Plant-Based}$					*0.004****	*0.008****
β_{Shrimp}					*0.031****	*0.12****
β_{Salmon}					*0.068****	*0.29****
λ_{Ribeye}					*-1.008*	*-0.79*
$\lambda_{Hamburger}$					*-28.765†††*	*-40.266†††*
$\lambda_{Pork\ Chop}$					*-30.615†*	*-25.874††*
$\lambda_{Baby\ Back\ Ribs}$					*-1.615†††*	*-1.246*
$\lambda_{Chicken\ Breast}$					*-34.746†††*	*-113.281†††*
$\lambda_{Plant-Based}$					*-16.66†††*	*-28.028†††*
λ_{Shrimp}					*-2.425†††*	*-1.802††*
λ_{Salmon}					*-1.212*	*-0.952*

Statistical Significance:
For tests with a null of 0: (***) indicates $p<0.01$; (**) indicates $p<0.05$; (*) indicates $p<0.10$.
For tests with a null of $|1|$: (†††) indicates $p<0.01$; (††) indicates $p<0.05$; (†) indicates $p<0.10$.
§These models successfully converged. However, some eigenvalues of Hessian were positive. This could point to an identification or estimation problem. Potentially thin data for some groups segmented by control variables.

Own-Price Elasticity Estimates

Using estimated model coefficients, I obtained elasticity estimates both above and below the mean reference price. These estimates are contained in tables 1.12, 1.13, 1.14, and 1.15. The first two blocks of rows in these tables are the elasticity estimates themselves, the next block contains the difference between above and below the reference price, the last block compares these differences to the linear baseline model. This allows readers to compare price sensitivity in gains and losses while also understanding the model choice implications.

Table 1.12: Own-Price Elasticity Estimates for Models with Common RPEs (Retail)

	Ribeye Steak	**Ground Beef**	**Pork Chop**	**Bacon**	**Chicken Breast**	**Plant Based Patty**	**Shrimp**	**Beans & Rice**
				Elasticity losses				
BL	*-2.41*	*-1.33*	*-1.49*	*-1.89*	*-0.98*	*-1.80*	*-2.16*	*-0.64*
SS	*-2.41*	*-1.32*	*-1.49*	*-1.88*	*-0.96*	*-1.78*	*-2.14*	*-0.63*
LA	*-3.07*	*-1.47*	*-1.67*	*-2.09*	*-1.08*	*-2.09*	*-2.64*	*-0.72*
LADS	*-6.35*	*-2.21*	*-2.54*	*-3.17*	*-1.62*	*-4.23*	*-4.99*	*-1.16*
				Elasticity Gains				
BL	*-2.38*	*-1.32*	*-1.47*	*-1.87*	*-0.97*	*-1.78*	*-2.13*	*-0.63*
SS	*-2.38*	*-1.30*	*-1.47*	*-1.85*	*-0.95*	*-1.76*	*-2.11*	*-0.63*
LA	*-1.67*	*-1.13*	*-1.27*	*-1.63*	*-0.81*	*-1.25*	*-1.65*	*-0.52*
LADS	*-1.41*	*-1.00*	*-1.13*	*-1.50*	*-0.69*	*-1.16*	*-1.43*	*-0.42*
				Difference (Gain-Loss)*				
BL	*0.03*	*0.02*	*0.02*	*0.02*	*0.01*	*0.02*	*0.02*	*0.01*
SS	*0.03*	*0.02*	*0.02*	*0.02*	*0.01*	*0.02*	*0.02*	*0.01*
LA	*1.40*	*0.34*	*0.40*	*0.46*	*0.27*	*0.84*	*0.99*	*0.20*
LADS	*4.94*	*1.21*	*1.42*	*1.67*	*0.93*	*3.08*	*3.56*	*0.74*
				*Difference in Differences** (vs BL)*				
SS	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
LA	*1.37*	*0.32*	*0.38*	*0.44*	*0.25*	*0.83*	*0.97*	*0.19*
LADS	*4.91*	*1.19*	*1.40*	*1.65*	*0.91*	*3.06*	*3.53*	*0.73*

Note: Elasticity estimates are only calculated for models with full set of control variables.
*Positive numbers imply greater price sensitivity in losses than gains
**Positive numbers imply greater difference between losses and gains than the baseline model.

Elasticities from models with a common reference price parameter across products, when applied to the retail dataset are shown in table 1.12. The baseline and sticker shock models have very similar elasticities, while estimates from asymmetric RPE models differ from the baseline. Consumers are more price sensitive in losses than gains. For example, the LA model for ribeye steak shows consumers respond by 1.4 percentage points more to a loss than a gain.

Table 1.13: Own-Price Elasticity Estimates for Models with Common RPEs (Food Service)

	Ribeye Steak	**Hamburger**	**Pork Chop**	**Baby Back Ribs**	**Chicken Breast**	**Plant Based Patty**	**Shrimp**	**Salmon**
				Elasticity losses				
BL	*-2.79*	*-1.41*	*-2.04*	*-3.13*	*-1.86*	*-2.13*	*-2.73*	*-2.86*
SS	*-2.81*	*-1.41*	*-2.03*	*-3.14*	*-1.86*	*-2.12*	*-2.74*	*-2.87*
LA	*-2.98*	*-1.41*	*-2.11*	*-3.28*	*-1.91*	*-2.19*	*-2.88*	*-3.02*
LADS	*-4.91*	*-2.13*	*-3.51*	*-4.75*	*-2.83*	*-3.34*	*-4.21*	*-4.60*
				Elasticity Gains				
BL	*-2.75*	*-1.39*	*-2.01*	*-3.09*	*-1.83*	*-2.11*	*-2.69*	*-2.82*
SS	*-2.77*	*-1.38*	*-2.00*	*-3.09*	*-1.83*	*-2.10*	*-2.71*	*-2.83*
LA	*-2.60*	*-1.29*	*-1.87*	*-2.98*	*-1.74*	*-1.99*	*-2.62*	*-2.71*
LADS	*-4.00*	*-1.82*	*-2.90*	*-4.04*	*-2.41*	*-2.85*	*-3.58*	*-3.85*
				Difference (Gain-Loss)*				
BL	*0.04*	*0.03*	*0.02*	*0.04*	*0.03*	*0.03*	*0.04*	*0.04*
SS	*0.04*	*0.03*	*0.02*	*0.04*	*0.03*	*0.03*	*0.04*	*0.04*
LA	*0.38*	*0.12*	*0.24*	*0.30*	*0.17*	*0.20*	*0.26*	*0.31*
LADS	*0.91*	*0.31*	*0.61*	*0.71*	*0.43*	*0.49*	*0.63*	*0.75*
				*Difference in Differences** (vs BL)*				
SS	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
LA	*0.34*	*0.10*	*0.22*	*0.25*	*0.14*	*0.17*	*0.22*	*0.27*
LADS	*0.87*	*0.28*	*0.58*	*0.67*	*0.40*	*0.47*	*0.59*	*0.71*

Note: Elasticity estimates are only calculated for models with full set of control variables.
*Positive numbers imply greater price sensitivity in losses than gains
**Positive numbers imply greater difference between losses and gains than the baseline model.

Elasticities from models with a common reference price parameter across products, when applied to the food service dataset are shown in table1.13. The baseline and sticker shock models have very similar elasticities, while estimates from asymmetric RPE models differ from the baseline. Consumers are more price sensitive in losses than gains. For example, the LA model for ribeye steak shows consumers respond by 0.38 percentage points more to a loss than a gain. Generally, food service estimates tend to be more elastic than retail. Additionally, the difference between gains and losses is smaller.

Table 1.14: Own-Price Elasticity Estimates for Models with Product Specific RPEs (Retail)

	Ribeye Steak	**Ground Beef**	**Pork Chop**	**Bacon**	**Chicken Breast**	**Plant Based Patty**	**Shrimp**	**Beans & Rice**
					Elasticity losses			
BL	*-2.41*	*-1.33*	*-1.49*	*-1.89*	*-0.98*	*-1.80*	*-2.16*	*-0.64*
SS	*-2.38*	*-1.32*	*-1.48*	*-1.88*	*-0.97*	*-1.77*	*-2.13*	*-0.63*
LA	*-2.57*	*-1.47*	*-1.87*	*-2.02*	*-1.28*	*-2.06*	*-2.75*	*-0.74*
LADS	*-4.91*	*-1.87*	*-2.17*	*-2.47*	*-1.80*	*-3.59*	*-5.81*	*-1.01*
					Elasticity Gains			
BL	*-2.38*	*-1.32*	*-1.47*	*-1.87*	*-0.97*	*-1.78*	*-2.13*	*-0.63*
SS	*-2.35*	*-1.30*	*-1.46*	*-1.85*	*-0.95*	*-1.75*	*-2.11*	*-0.62*
LA	*-2.39*	*-1.07*	*-1.16*	*-1.79*	*-0.63*	*-1.33*	*-1.46*	*-0.49*
LADS	*-4.25*	*-1.00*	*-1.15*	*-2.20*	*-0.60*	*-1.27*	*-1.29*	*-0.30*
					Difference (Gain-Loss)*			
BL	*0.03*	*0.02*	*0.02*	*0.02*	*0.01*	*0.02*	*0.02*	*0.01*
SS	*0.03*	*0.02*	*0.02*	*0.02*	*0.01*	*0.02*	*0.02*	*0.01*
LA	*0.17*	*0.39*	*0.70*	*0.23*	*0.65*	*0.72*	*1.29*	*0.25*
LADS	*0.67*	*0.87*	*1.02*	*0.27*	*1.20*	*2.33*	*4.52*	*0.71*
					*Difference in Differences** (vs BL)*			
SS	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
LA	*0.14*	*0.37*	*0.68*	*0.21*	*0.64*	*0.71*	*1.27*	*0.24*
LADS	*0.64*	*0.85*	*1.00*	*0.25*	*1.18*	*2.31*	*4.49*	*0.70*

Note: Elasticity estimates are only calculated for models with full set of control variables.
*Positive numbers imply greater price sensitivity in losses than gains
**Positive numbers imply greater difference between losses and gains than the baseline model.

Elasticities from models with a product specific RPE, when applied to the retail dataset are shown in table 1.14. The baseline and sticker shock models continue to have very similar elasticities, while estimates from asymmetric RPE models differ from the baseline. As before, consumers are more price sensitive in losses than gains. For example, the LA model for ribeye steak shows consumers respond by 0.17 percentage points more to a loss than a gain.

Table 1.15: Own-Price Elasticity Estimates for Models with Product Specific RPEs (Food Service)

	Ribeye Steak	**Hamburger**	**Pork Chop**	**Baby Back Ribs**	**Chicken Breast**	**Plant Based Patty**	**Shrimp**	**Salmon**
				Elasticity losses				
BL	*-2.79*	*-1.41*	*-2.04*	*-3.13*	*-1.86*	*-2.13*	*-2.73*	*-2.86*
SS	*-2.79*	*-1.38*	*-2.03*	*-3.12*	*-1.84*	*-2.11*	*-2.71*	*-2.89*
LA	*-2.83*	*-1.49*	*-2.43*	*-3.34*	*-1.86*	*-2.32*	*-3.03*	*-3.02*
LADS	*-4.83*	*-1.81*	*-4.95*	*-4.87*	*-2.36*	*-3.69*	*-4.44*	*-5.25*
				Elasticity Gains				
BL	*-2.75*	*-1.39*	*-2.01*	*-3.09*	*-1.83*	*-2.11*	*-2.69*	*-2.82*
SS	*-2.75*	*-1.35*	*-2.00*	*-3.07*	*-1.81*	*-2.09*	*-2.67*	*-2.85*
LA	*-2.78*	*-1.17*	*-1.34*	*-2.93*	*-1.57*	*-1.70*	*-2.46*	*-2.76*
LADS	*-5.68*	*-1.18*	*-1.26*	*-4.26*	*-1.50*	*-1.70*	*-3.28*	*-5.36*
				Difference (Gain-Loss)*				
BL	*0.04*	*0.03*	*0.02*	*0.04*	*0.03*	*0.03*	*0.04*	*0.04*
SS	*0.04*	*0.03*	*0.02*	*0.04*	*0.03*	*0.02*	*0.04*	*0.04*
LA	*0.05*	*0.32*	*1.09*	*0.40*	*0.29*	*0.62*	*0.58*	*0.25*
LADS	*-0.84*	*0.64*	*3.69*	*0.62*	*0.86*	*1.99*	*1.16*	*-0.11*
				*Difference in Differences** (vs BL)*				
SS	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
LA	*0.01*	*0.29*	*1.07*	*0.36*	*0.26*	*0.60*	*0.54*	*0.22*
LADS	*-0.88*	*0.61*	*3.66*	*0.57*	*0.83*	*1.96*	*1.12*	*-0.15*

Note: Elasticity estimates are only calculated for models with full set of control variables.
*Positive numbers imply greater price sensitivity in losses than gains
**Positive numbers imply greater difference between losses and gains than the baseline model.

Elasticities from models with a product specific RPE, when applied to the food service dataset are shown in table 1.15. The baseline and sticker shock models have very similar elasticities, while estimates from asymmetric RPE models differ from the baseline. Consumers are more price sensitive in losses than gains. For example, the LA model for ribeye steak shows consumers respond by 0.05 percentage points more to a loss than a gain. Generally, food service estimates tend to be more elastic than retail.

Market Share and Consumer Welfare Predictions

Using estimated model coefficients and mean reference prices, I predicted the impact of a 10% change to chicken prices. I show the impacts in terms of market share changes and consumer welfare impact. The first block of rows in the market share tables shows the predicted market shares at the mean reference prices. The second and third blocks show the change in market share given the price change, first for a price decrease then for an increase. In consumer welfare tables, the first block of rows shows welfare changes for a price decrease, while the second block shows welfare changes for a price increase. It is useful to compare the preferred model to the baseline to determine how much the predictions differ. This helps us answer the question of whether the improved model performance is economically significant.

Market share predictions for models with a common RPE using the retail dataset are displayed in table 1.16. Models with loss aversion predict larger market share changes for chicken when the price increases than when it decreases. Additionally, RPEs affect the market shares for other products whose price is not changing. Typically, a price increase impacts these products more than a decrease because loss aversion causes more substitution to occur.

Table 1.16: Market Share Predictions for Models with Common RPE Parameters (Retail)

	Ribeye Steak	**Ground Beef**	**Pork Chop**	**Bacon**	**Chicken Breast**	**Plant Based Patty**	**Shrimp**	**Beans & Rice**	**None of These**
					At Reference Prices				
BL	7.38%	20.73%	13.84%	8.38%	26.31%	3.21%	4.93%	8.21%	7.02%
SS	7.10%	20.64%	13.55%	8.35%	26.79%	3.19%	4.94%	8.38%	7.07%
LA	7.56%	21.20%	13.88%	8.51%	25.99%	3.38%	5.01%	8.01%	6.46%
LADS	7.61%	20.82%	14.25%	8.33%	26.38%	3.42%	5.36%	8.05%	5.78%
					Change (Chicken Price -10%)				
BL	-0.29%	-0.82%	-0.55%	-0.33%	2.93%	-0.13%	-0.20%	-0.33%	-0.28%
SS	-0.29%	-0.83%	-0.55%	-0.34%	2.95%	-0.13%	-0.20%	-0.34%	-0.28%
LA	-0.26%	-0.72%	-0.47%	-0.29%	2.52%	-0.11%	-0.17%	-0.27%	-0.22%
LADS	-0.23%	-0.64%	-0.43%	-0.25%	2.25%	-0.10%	-0.16%	-0.25%	-0.18%
					Change (Chicken Price +10%)				
BL	0.27%	0.77%	0.51%	0.31%	-2.73%	0.12%	0.18%	0.30%	0.26%
SS	0.27%	0.78%	0.51%	0.31%	-2.76%	0.12%	0.19%	0.32%	0.27%
LA	0.31%	0.88%	0.57%	0.35%	-3.07%	0.14%	0.21%	0.33%	0.27%
LADS	0.46%	1.25%	0.85%	0.50%	-4.41%	0.21%	0.32%	0.48%	0.35%

Consumer welfare impacts are shown in table 1.17. Impacts on consumer welfare differ significantly across models. Furthermore, models incorporating loss aversion have larger differences between price increases and decreases than the baseline. For example, the LA model predicts a $750,800,399 national change with a price decrease and a -$906,178,075 change with a price increase, a 5.1% and a 37.3% increase over the baseline prediction respectively.

Table 1.17: Consumer Welfare Predictions for Models with Common RPE Parameters (Retail)

	Per Choice	Per Household * Annually	Total US** Annually	Difference vs BL	Pct Difference vs BL
			Change (Chicken Price -10%)		
BL	$0.11	$5.93	$734,997,259	$0	0.0%
SS	$0.14	$7.40	$918,021,543	$183,024,284	24.9%
LA	$0.12	$6.23	$772,286,168	$37,288,909	5.1%
LADS	$0.12	$6.05	$750,800,399	$15,803,140	2.2%
			Change (Chicken Price +10%)		
BL	-$0.10	-$5.32	-$660,102,979	$0	0.0%
SS	-$0.13	-$6.65	-$825,265,422	-$165,162,443	25.0%
LA	-$0.14	-$7.31	-$906,178,075	-$246,075,096	37.3%
LADS	-$0.22	-$11.37	-$1,410,015,566	-$749,912,587	113.6%

*Assuming one choice encounter per week.
**Assuming one choice situation per week for each of 124,010,992 US households (US Census Bureau, 2021).

Market share predictions for models with a common RPE using the food service dataset are displayed in table 1.18. As before, models with loss aversion predict larger market share changes for chicken when the price increases than when it decreases. Additionally, RPEs impact the market shares for other products whose price is not changing. Typically, a price increase impacts these products more than a decrease because loss aversion causes more substitution to occur. For example, the LA model predicts a change in market share of 3.83% for a price decrease and a change of -3.56% for a price increase.

Table 1.18: Market Share Predictions for Models with Common RPE Parameters (Food Service)

	Ribeye Steak	Hamburger	Pork Chop	Baby Back Ribs	Chicken Breast	Plant Based Patty	Shrimp	Salmon	None of These
					At Reference Prices				
BL	8.72%	32.96%	5.33%	7.21%	19.00%	5.83%	8.82%	6.76%	5.37%
SS	8.70%	32.94%	5.42%	7.17%	19.14%	5.92%	8.66%	6.73%	5.31%
LA	9.15%	33.71%	5.28%	7.12%	18.83%	5.72%	8.50%	6.65%	5.04%
LADS	10.10%	32.03%	5.44%	7.40%	18.74%	5.72%	8.92%	7.21%	4.45%
					Change (Chicken Price -10%)				
BL	-0.44%	-1.66%	-0.27%	-0.36%	4.08%	-0.29%	-0.44%	-0.34%	-0.27%
SS	-0.44%	-1.67%	-0.27%	-0.36%	4.10%	-0.30%	-0.44%	-0.34%	-0.27%
LA	-0.43%	-1.59%	-0.25%	-0.34%	3.83%	-0.27%	-0.40%	-0.31%	-0.24%
LADS	-0.57%	-1.82%	-0.31%	-0.42%	4.62%	-0.32%	-0.51%	-0.41%	-0.25%
					Change (Chicken Price +10%)				
BL	0.38%	1.43%	0.23%	0.31%	-3.50%	0.25%	0.38%	0.29%	0.23%
SS	0.38%	1.44%	0.24%	0.31%	-3.53%	0.26%	0.38%	0.29%	0.23%
LA	0.40%	1.48%	0.23%	0.31%	-3.56%	0.25%	0.37%	0.29%	0.22%
LADS	0.54%	1.71%	0.29%	0.39%	-4.33%	0.30%	0.48%	0.38%	0.24%

Consumer welfare impacts are shown in table 1.19. Impacts on consumer welfare differ significantly across models. Furthermore, models incorporating loss aversion have larger differences between price increases and decreases than the baseline. For example, the LA model predicts a $2,065,874,534 national change in consumer surplus with a price decrease and a -$1,836,079,468 change with a price increase, a 24.1% and a 34.6% increase over the baseline prediction respectively.

Table 1.19: Consumer Welfare Predictions for Models with Common RPE Parameters (Food Service)

	Per Choice	Per Household * Annually	Total US** Annually	Difference vs BL	Pct Difference vs BL
Change (Chicken Price -10%)					
BL	$0.26	$13.42	$1,664,127,771	$0	0.0%
SS	$0.34	$17.72	$2,197,918,799	$533,791,027	32.1%
LA	$0.32	$16.66	$2,065,874,534	$401,746,763	24.1%
LADS	$0.43	$22.12	$2,743,581,570	$1,079,453,798	64.9%
Change (Chicken Price +10%)					
BL	-$0.21	-$11.00	-$1,363,612,285	$0	0.0%
SS	-$0.28	-$14.53	-$1,801,663,241	-$438,050,956	32.1%
LA	-$0.28	-$14.81	-$1,836,079,468	-$472,467,183	34.6%
LADS	-$0.38	-$19.62	-$2,433,594,060	-$1,069,981,775	78.5%

*Assuming one choice encounter per week.
**Assuming one choice situation per week for each of 124,010,992 US households (US Census Bureau, 2021).

Market share predictions for models with a product specific RPE using the retail dataset are displayed in table 1.20. As before, models with loss aversion predict larger market share changes for chicken when the price increases than when it decreases. Additionally, RPEs impact the market shares for other products whose price is not changing. Typically, a price increase impacts these products more than a decrease because loss aversion causes more substitution to occur. For example, the LA model predicts a change in market share of 2.14% for a price decrease and a change of -4.02% for a price increase.

Table 1.20: Market Share Predictions for Models with Product Specific RPE Parameters (Retail)

	Ribeye Steak	Ground Beef	Pork Chop	Bacon	Chicken Breast	Plant Based Patty	Shrimp	Beans & Rice	None of These
					At Reference Prices				
BL	7.38%	20.73%	13.84%	8.38%	26.31%	3.21%	4.93%	8.21%	7.02%
SS	7.46%	20.71%	13.76%	8.31%	26.30%	3.31%	4.90%	8.23%	7.03%
LA	5.72%	21.39%	14.11%	7.66%	28.95%	2.98%	5.08%	7.94%	6.17%
LADS	5.90%	21.23%	14.33%	7.16%	28.36%	3.33%	5.60%	8.13%	5.94%
					Change (Chicken Price -10%)				
BL	-0.29%	-0.82%	-0.55%	-0.33%	2.93%	-0.13%	-0.20%	-0.33%	-0.28%
SS	-0.29%	-0.82%	-0.54%	-0.33%	2.91%	-0.13%	-0.19%	-0.32%	-0.28%
LA	-0.17%	-0.64%	-0.43%	-0.23%	2.14%	-0.09%	-0.15%	-0.24%	-0.19%
LADS	-0.17%	-0.62%	-0.42%	-0.21%	2.08%	-0.10%	-0.16%	-0.24%	-0.17%
					Change (Chicken Price +10%)				
BL	0.27%	0.77%	0.51%	0.31%	-2.73%	0.12%	0.18%	0.30%	0.26%
SS	0.27%	0.76%	0.51%	0.31%	-2.71%	0.12%	0.18%	0.30%	0.26%
LA	0.32%	1.21%	0.80%	0.43%	-4.02%	0.17%	0.29%	0.45%	0.35%
LADS	0.42%	1.52%	1.03%	0.51%	-5.13%	0.24%	0.40%	0.58%	0.43%

Consumer welfare impacts are shown in table 1.21. Impacts on consumer welfare differ significantly across models. Furthermore, models incorporating loss aversion have larger differences between price increases and decreases than the baseline. For example, the LA model predicts a $720,406,753 national change in consumer surplus with a price decrease and a -$1,295,843,014 change with a price increase, a 24.1% and a 34.6% increase over the baseline prediction respectively.

Table 1.21: Consumer Welfare Predictions for Models with Product Specific RPE Parameters (Retail)

	Per Choice	Per Household * Annually	Total US** Annually	Difference vs BL	Pct Difference vs BL
			Change (Chicken Price -10%)		
BL	$0.11	$5.93	$734,997,259	$0	0.0%
SS	$0.14	$7.15	$886,213,551	$151,216,293	20.6%
LA	$0.11	$5.81	$720,406,753	-$14,590,505	-2.0%
LADS	$0.11	$5.72	$709,154,170	-$25,843,088	-3.5%
			Change (Chicken Price +10%)		
BL	-$0.10	-$5.32	-$660,102,979	$0	0.0%
SS	-$0.12	-$6.42	-$796,378,370	-$136,275,392	20.6%
LA	-$0.20	-$10.45	-$1,295,843,014	-$635,740,035	96.3%
LADS	-$0.26	-$13.44	-$1,666,605,060	-$1,006,502,081	152.5%

*Assuming one choice encounter per week.
**Assuming one choice situation per week for each of 124,010,992 US households (US Census Bureau, 2021).

Market share predictions for models with a product specific RPE using the food service dataset are displayed in table 1.22. As before, models with loss aversion predict larger market share changes for chicken when the price increases than when it decreases. Additionally, RPEs impact the market shares for other products whose price is not changing. Typically, a price increase impacts these products more than a decrease because loss aversion causes more substitution to occur. For example, the LA model predicts a change in market share of 3.51% for a price decrease and a change of -3.56% for a price increase.

Table 1.22: Market Share Predictions for Models with Product Specific RPE Parameters (Food Service)

	Ribeye Steak	Hamburger	Pork Chop	Baby Back Ribs	Chicken Breast	Plant Based Patty	Shrimp	Salmon	None of These
					At Reference Prices				
BL	8.72%	32.96%	5.33%	7.21%	19.00%	5.83%	8.82%	6.76%	5.37%
SS	8.57%	33.77%	5.19%	7.09%	19.12%	5.82%	8.88%	6.32%	5.23%
LA	8.11%	33.73%	6.04%	6.97%	19.13%	5.86%	9.10%	6.18%	4.88%
LADS	8.94%	32.83%	6.13%	7.03%	19.61%	6.13%	8.72%	6.30%	4.32%
					Change (Chicken Price -10%)				
BL	-0.44%	-1.66%	-0.27%	-0.36%	4.08%	-0.29%	-0.44%	-0.34%	-0.27%
SS	-0.43%	-1.70%	-0.26%	-0.36%	4.08%	-0.29%	-0.45%	-0.32%	-0.26%
LA	-0.35%	-1.47%	-0.26%	-0.30%	3.51%	-0.25%	-0.40%	-0.27%	-0.21%
LADS	-0.38%	-1.41%	-0.26%	-0.30%	3.44%	-0.26%	-0.37%	-0.27%	-0.19%
					Change (Chicken Price +10%)				
BL	0.38%	1.43%	0.23%	0.31%	-3.50%	0.25%	0.38%	0.29%	0.23%
SS	0.37%	1.46%	0.23%	0.31%	-3.51%	0.25%	0.38%	0.27%	0.23%
LA	0.36%	1.48%	0.27%	0.31%	-3.56%	0.26%	0.40%	0.27%	0.21%
LADS	0.46%	1.69%	0.31%	0.36%	-4.13%	0.31%	0.45%	0.32%	0.22%

Consumer welfare impacts are shown in table 1.23. Impacts on consumer welfare differ significantly across models. Furthermore, models incorporating loss aversion have larger differences between price increases and decreases than the baseline. For example, the LA model predicts a $1,832,417,492 national change in consumer surplus with a price decrease and a -$1,775,552,404 change with a price increase, a 10.1% and a 30.2% increase over the baseline prediction respectively.

Table 1.23: Consumer Welfare Predictions for Models with Product Specific RPE Parameters (Food Service)

	Per Choice	Per Household* Annually	Total US** Annually	Difference vs BL	Pct Difference vs BL
			Change (Chicken Price -10%)		
BL	$0.26	$13.42	$1,664,127,771	$0	0.0%
SS	$0.32	$16.88	$2,093,310,704	$429,182,932	25.8%
LA	$0.28	$14.78	$1,832,417,492	$168,289,720	10.1%
LADS	$0.30	$15.79	$1,958,034,516	$293,906,744	17.7%
			Change (Chicken Price +10%)		
BL	-$0.21	-$11.00	-$1,363,612,285	$0	0.0%
SS	-$0.27	-$13.85	-$1,717,601,607	-$353,989,322	26.0%
LA	-$0.28	-$14.32	-$1,775,552,404	-$411,940,119	30.2%
LADS	-$0.35	-$18.07	-$2,240,772,926	-$877,160,641	64.3%

*Assuming one choice encounter per week.
**Assuming one choice situation per week for each of 124,010,992 US households (US Census Bureau, 2021).

Discussion

The results of this essay are in line with the previous literature in which evidence for loss aversion has been consistently found (Neumann & Böckenholt, 2014). My results demonstrate that models with reference price effect perform better than those without when subjected to out-of-sample validation. Additionally, I find RPE coefficients to be statistically significant in most cases. These results hold true across market channels and product categories. Moreover, I add to the literature by demonstrating the economic significance of these results. Loss aversion in particular impacts elasticities, market share predictions, and consumer welfare calculations. I also contribute by systematically comparing different types of RPEs and applying these models to a previously unstudied product category across marketing channels.

For models with a common parameter, the estimates are -47.71 for retail and -1.33 for food service. For models with product specific parameters, the estimates range from -1.19 to -299.80 in the retail setting and from -0.79 to -113.28 in the food service setting. The estimates for retail are consistently larger than analogous parameters in food service. This is partially driven by a smaller gain parameter for retail, which increases the loss aversion ratio. This result may be partially driven by the fact that retail consumers were restricted to a discrete choice, whereas in a real retail setting they could purchase a larger quantity in response to a gain.

One important implication of my analysis is that any policy to reduce volatility in food prices benefits consumers more if it focuses on limiting price increases. This point is more important in the retail setting than it is in the food service setting, based on the results in this essay. My results also demonstrate that analysis of a price stability policy will not value consumer welfare correctly without including reference price effects. The predicted impact of a price increase on consumer welfare was sometimes nearly double the baseline prediction, underscoring the economic significance of accounting for RPEs.

In the conceptual framework of this essay there are figures illustrating the differences in utility functions for each hypothesis. Since the models in this essay are estimating utility functions, we can plot them to visually compare with the figures from the conceptual framework. For example, figure 1.12 combines the utility functions for the baseline model with those that include common parameters across products with RPEs for shrimp in the retail setting. It is easy to see the kink in utility for both the LA and LADS model. Additionally, the curvature in the LADS model is also evident. The consumers utility function is directly related to the demand function, which is shown in figure 1.13. The kinks in the LA and LADS models are visible at the reference price. This leads to the difference in demand elasticities on either side of the reference price, as was observed in the results section. These illustrations visually demonstrate the differences in demand elasticities and consumer welfare impacts that were shown in the results section.

In summary, the results of this study have implications for economic research, policy analysis, and business strategy. Whenever an analyst wants to measure the impact of an event, policy, or strategic decision on the protein market, demand relationships are at the core of the analysis. These demand relationships have an abrupt change at the consumers reference price. I have shown in this essay that failing to recognize this can lead to large predictive errors.

Figure 1.12: Shrimp Retail Utility with Common RPE

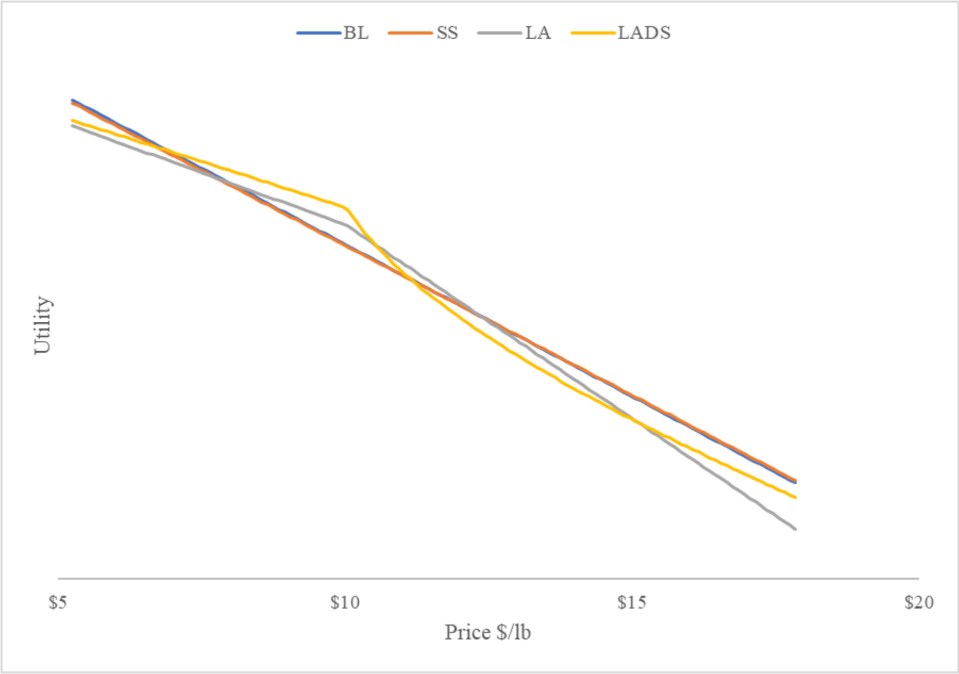
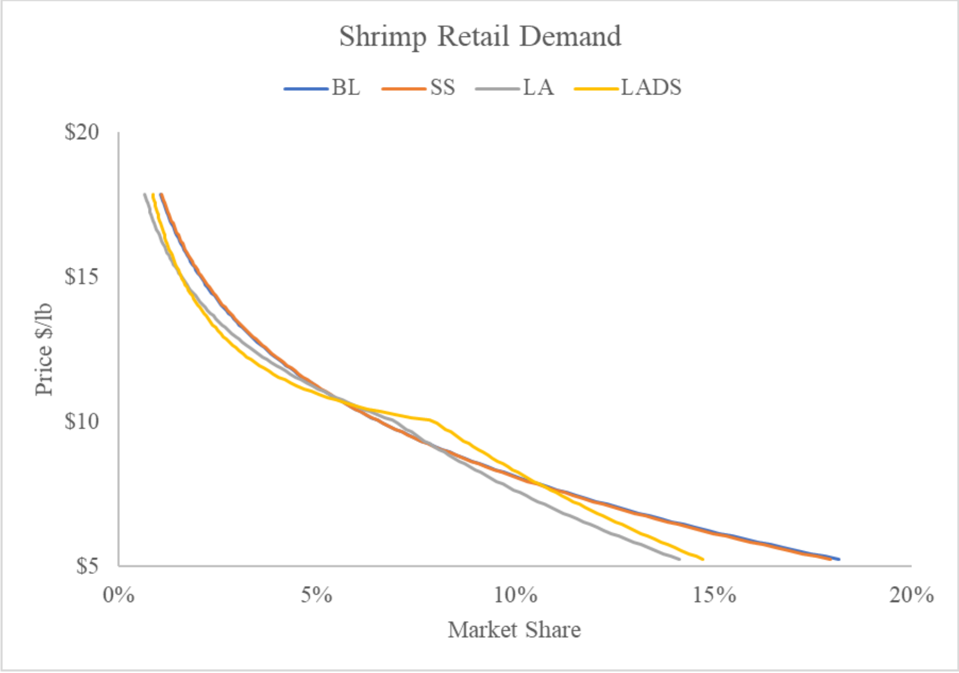


Figure 1.13: Shrimp Retail Demand with Common RPE



Summary and Conclusion

In this essay I have tested for reference price effects in consumer choice for protein and demonstrated the implications in post-estimation analysis. I leveraged choice experiment data in a random utility framework while progressively incorporating various reference price features and found that reference price effects improve model performance, both within and outside of the estimation sample. The magnitude of reference price effects varies by product and across marketing channels, with implications for elasticity estimates, market share predictions, and welfare analysis. My results are consistent with previous research but add an application to a previously unstudied product group across market channels, while also demonstrating the implications of several types of RPEs. This additional information provides insights into protein markets and important guidance to researchers and policy analysts.

Future research could apply these models to understand the market impact of animal disease outbreaks. Additionally, future work could examine the welfare impact of losing food service options in the light of loss aversion. This essay does have several limitations. One is that the data is choice experiment data and there is little indication of the quantity that a respondent would purchase. However, This essay does serve to fill several knowledge gaps and provides a new application of RPEs in choice models.

Chapter 2 - Impacts of Subsidized Pasture Insurance on Land Value and Use

Introduction

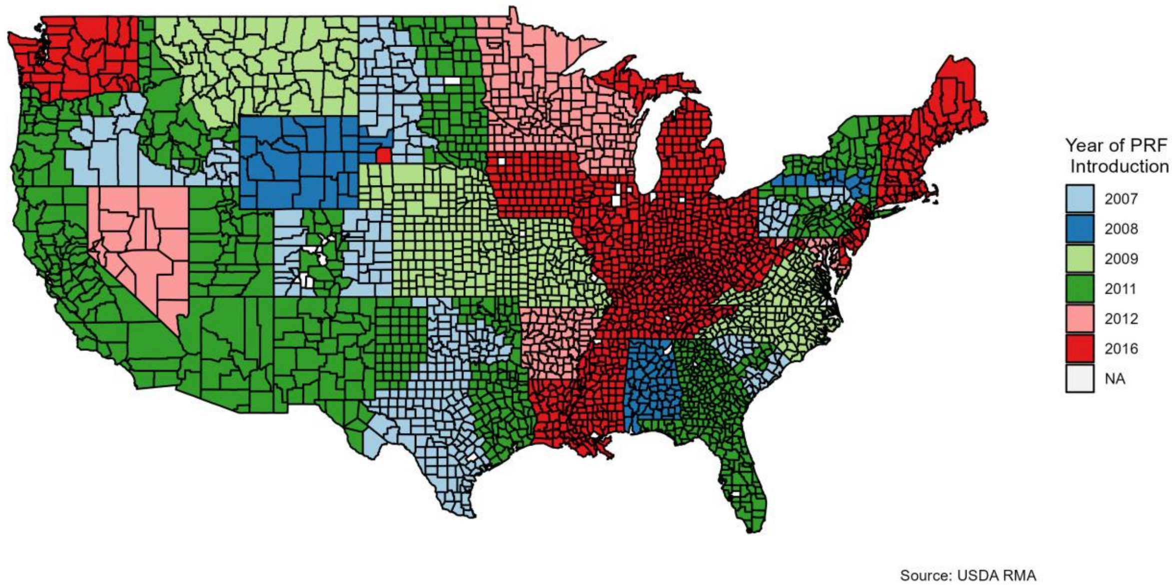
Benefits of government subsidized farm programs may 'pass through' production agriculture to input prices. However, which agricultural inputs are most impacted depends on input supply elasticities, factor substitution elasticities, and output demand elasticity (Alston et al., 2002; Floyd, 1965; B. L. Gardner, 1987). In particular, the smaller the relative elasticity of supply for an input, the larger the proportional value of the subsidy will pass through to that input. Among agricultural inputs, land is relatively inelastic in supply, often leading to high rates of subsidy capitalization to land value. Such effects have long been of interest to policy makers as the benefits of a program may accrue differently for different groups of producers. Although some producers may also be landowners, many rent the land on which they operate. For tenant producers, the value of the program is reduced because they do not receive an increase in asset value on their balance sheet and may face higher rent. Furthermore, high land prices are also a barrier to entry to beginning farmers because of elevated capital requirements to purchase land. Consequently, the value of publicly supported farm programs may not have the intended distribution of benefits.

Similarly, agricultural risk management programs which are subsidized by the federal government can increase expected future revenue and reduce risk, potentially impacting land values via land use decisions. The potential benefit to producers from subsidized insurance programs is twofold. First, the availability of insurance benefits risk averse producers. The value of reduced risk is greater than the cost of insurance for those who voluntarily choose to enroll. This is true even if the insurance premium is actuarily fair or larger. Reduced risk may result in higher output, potentially driving different input allocations including land use changes. Secondly, most agricultural insurance programs in the US are subsidized by the federal government, leading to actuarially unfair premiums in favor of the producer. In other words, the present value of expected indemnities is larger than the premium. Meaning that producers increase their expected future profits by enrolling in subsidized insurance programs. If the program applies to only a subset of land uses, the subsidy will act like a demand increase for those commodities to which it applies, potentially altering input allocations including land use. Thus, risk management programs could change land use decisions, in turn driving changes in land values.

As an agricultural risk management program, Pasture, Rangeland, and Forage (PRF) Index Insurance has the potential to impact agricultural land use and value. Therefore, the objective of this study is to measure the impact of PRF on both pastureland area and value. I expect PRF insurance to increase the quantity of land used for pasture and the value of pastureland because it applies to only a narrow subset of land uses such as pasture and forage. Due to data availability, I used agricultural land values as a proxy for pastureland values, because I believe they are closely related. However, the impact on farmland values is likely a conservative estimate of the effect on pastureland values. The effect of PRF insurance is likely geographically heterogenous based on the local elasticity of pastureland supply. The local pastureland supply elasticity reflects the marginal cost of transitioning land from another use to pasture; a portion of which is the opportunity cost of the land. In areas of the country that have a high percentage of public lands, there is a relatively abundant supply of potential pastureland with few alternative uses (i.e., typically public land cannot be farmed but may be grazed by livestock). Consequently, the presence of public land may increase the elasticity of supply for pastureland. Therefore, I investigated heterogeneity in the effects of PRF across counties with different proportions of public land in addition to the average effects of PRF.

To achieve the objective of this study, I leveraged the staggered rollout of PRF at the county level in a non-traditional Difference-in-Differences framework and found a positive effect on both farmland value and acres of pastureland. Identification strategies for the effect of farm policies can be difficult, especially if the policy was introduced at a national scale. However, the PRF insurance program was introduced in a staggered rollout as shown in figure 2.1. This provided variation across counties and time that were exploited in a non-traditional difference-in-differences design. Unfortunately, the standard two-way fixed effects (TWFE) estimator may not be the best approach in this case, as it is only valid for two time periods and assumes treatment effect homogeneity (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). As a result I chose to use the two-stage difference-in-differences (2SDiD) estimator, which is robust to treatment timing and treatment effect heterogeneity (J. Gardner, 2022). The 2SDiD estimates for the average effect of PRF availability was 7.6% for land value and 9.6% for pasture acres over a period of about 3 years. These results are in line with my theoretical analysis, while also consistent with the results from a small body of previous research (Ifft et al., 2014; Yu et al., 2022).

Figure 2.1: Year of PRF Introduction



The estimated effects of PRF were heterogenous across counties with different proportions of public land. This is an important source of heterogeneity because the proportion of public land varies geographically, creating regions where the effect of PRF is quite different from the average effect. Higher percentages of public land in a county were associated with smaller effects on land value. The interaction effect of public lands and PRF availability on pasture area was not monotonic. However, comparing counties with in the first quartile of proportional public land area with counties in the fourth quartile, the effect of PRF availability in the fourth quartile was larger. These results are essentially consistent with theoretical analysis, assuming the presence of public land makes pastureland supply more elastic.

The remainder of this article is organized as follows: the next section contains a review of relevant literature, followed by a description of the data, the theory and methods used, results of the analysis, a discussion of the results and implications, and finally concluding comments.

Previous Literature

Much literature has focused on the pass through of government subsidies into land values, with most studies finding positive capitalization rates (Latruffe & Le Mouël, 2009). However, estimates vary with different approaches and levels of data aggregation (Kirwan & Roberts, 2016). A constant theme is that government support typically does pass through to input markets, yet the magnitude of the effect is highly variable across studies.

Research has examined the effect of federal crop insurance on land use, typically finding that crop insurance increased cropland by a small amount. For example, Claassen et al. (2017) found that crop insurance increased cropland acreage by 0.18%, while pasture and CRP acreage decreased by 1.07% and 0.23%, respectively. Similarly, Goodwin et al. (2004) found a positive effect of crop insurance on cropland brought into production. Yet, they estimated that a 30% reduction in premiums due to increased subsidies would result in a mere 0.2% to 1.1% impact on crop acres. The relatively small magnitude of these effects points toward a small elasticity of supply for cropland. Overall, these studies establish a connection between subsidized crop insurance and land use changes as farmers respond to adjusted incentives.

Turning specifically to PRF insurance, very few studies have reported effects on land use resulting from this particular program. However, Yu et al., (2022) studied the effect of PRF availability on Conservation Reserve Program (CRP) enrollment. They found that the availability of PRF insurance had a negative impact on CRP enrollment, and an increasing effect with length of exposure. Further, they documented group specific effects for each treatment group as it entered the program. While their analysis shows an impact on land use from PRF, it doesn't show the full pastureland quantity effect because the objective of the paper is centered on CRP enrollment. This essay adds to their analysis by looking at land converted to pasture from any source.

Studies that explore the effect of PRF insurance on land value are similarly scarce. However, Ifft et al., (2014) explored the impact of this program on farmland values using tract level survey data reported by farmers. They exploited the staggered rollout of the program to estimate the treatment effect using a TWFE approach. They found that the availability of PRF insurance was associated with at least a 4 percent increase in pastureland value. However, they did not explore land use impacts or sources of effect heterogeneity. Furthermore, TWFE has since been shown to be potentially biased in the presence of treatment effect heterogeneity and staggered treatment timing (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). This essay adds to the work of Ifft et al., (2014) by examining both land value and land use effects, using a potentially more robust econometric method.

In conclusion, previous literature has identified price and quantity effects associated with PRF. Results show that pastureland acres increase as well as land values. However, there has not been a study that addressed land value and use in conjunction with each other. Furthermore, sources of heterogeneity in the effects have not been addressed adequately. This essay adds to the previous literature by estimating the impact of PRF insurance on both farmland values and pasture acres, while also assessing the interaction effect of public land.

Methods & Data

Background Information

The PRF insurance program is a risk management program for livestock producers and forage growers (Carvalho et al., 2019). This program is unique from other crop insurance programs because the mechanism for triggering an indemnity payment is not tied to losses. Rather, indemnities are triggered when the rainfall[6] index falls below a pre-defined threshold level. The rainfall index is measured on a grid where each unit is approximately 17x17 miles. Producers select how many acres to enroll and a coverage level. If an indemnity is triggered, payments depend on a productivity factor and insurable interest (e.g. under a revenue sharing rental agreement both the land-lord and tenant will have insurable interest in the livestock). Importantly, indemnity payments are not connected to market prices or crop losses. In addition, the program is subsidized so that premiums are lower than the expected value of indemnities. Because enrollment is only available on land used to graze livestock or grow forage crops, there becomes an incentive to increase land allocated for these purposes. Thus we consider PRF availability as a demand shifter for land as an input for livestock production.

Conceptual Framework

My theoretical analysis of the impact of PRF insurance consists of a partial equilibrium model for the pastureland market as an input to livestock production. In contrast, previous theoretical work on subsidy capitalization typically includes demand and supply for several inputs and an output of a given commodity (Alston et al., 2002; Floyd, 1965; B. L. Gardner,

[6] Early in the program, a vegetative index was used in some counties. All counties eventually transitioned to utilizing a rainfall index.

1987). This more complete approach allows analysis of the relative pass-through rates among various inputs. However, for my analysis I simplify the model to a single market. My simplified approach is appropriate because I seek to determine the directional impact of PRF on price and quantity of pastureland, rather than relative input pass through rates. Furthermore, this analysis also demonstrates the effect of changing the input supply elasticity on the size of price and quantity effects. In summary, my analysis of a single market for pastureland meets the objectives of this study without undue complexity.

My conceptual model is focused on the impact of PRF insurance availability, which I model as an exogenous increase in the factor demand for pastureland. PRF insurance may act as a demand shifter in the pastureland market by reducing risk to producers, increasing expected future profits, or both. First, reducing uncertainty for risk averse producers could increase their choice of output, increasing factor demand. The increase in output can occur because risk averse agents faced with uncertainty produce at a quantity such that marginal cost is less than marginal revenue (Silberberg & Suen, 2000). The implication of this condition is that quantity produced increases in inverse proportion to decreasing uncertainty, assuming increasing marginal costs. Therefore, when a risk management program becomes available, uncertainty could be reduced and output may increase, in turn causing input demand to increase. Secondly, most agricultural insurance programs in the US are subsidized by the federal government, leading to actuarially unfair premiums in favor of the producer. In other words, the present value of expected indemnities is larger than the premium, implying that producers increase their expected future profits by enrolling. Because of the direct connection to acres used for pasture and forage, PRF can cause an increase in demand for land. Thus, there are potential impacts on land use (quantity effect), land values (price effect), or both.

My partial equilibrium analysis of the impacts of PRF insurance availability on land use and land value begins with linear inverse demand and supply functions for pastureland in equations 1 and 2,

$$P_i = \theta_{Di} - \delta_{Di} Q_{Di}, \tag{1}$$

$$P_i = \theta_{Si} + \delta_{Si} Q_{Si}. \tag{2}$$

Where P_i is the local price of pastureland in county i, Q_{Di} and Q_{Si} are quantity of pastureland demanded and quantity supplied in county i, θ_{Di} and θ_{Si} are demand and supply intercept parameters for county i, while $\delta_{Di} > 0$ and $\delta_{Si} > 0$ are demand and supply slope parameters in county i. For simplicity I suppress the i subscript from this point forward. Equation 1 represents the factor demand of livestock production, while equation 2 represents the supply of pastureland from landowners. Solving for the equilibrium price and quantity, I obtain equations 3 and 4,

$$Q^* = \frac{\theta_D - \theta_S}{\delta_S + \delta_D}, \tag{3}$$

$$P^* = \theta_S + \frac{\delta_S(\theta_D - \theta_S)}{\delta_S + \delta_D}. \tag{4}$$

Using the formulas for Q^* and P^* I can evaluate the impact of an exogenous increase in the demand for pastureland, such as the introduction of PRF insurance. A positive shift in demand can be expressed by changing the baseline demand intercept, θ_D^0 to a new intercept θ_D^1, such that $\theta_D^1 \geq \theta_D^0$. The resulting change in equilibrium quantity, $\Delta Q^* = Q^{*1} - Q^{*0}$, and equilibrium price, $\Delta P^* = P^{*1} - P^{*0}$, simplify to the following expressions,

$$\Delta Q^* = \frac{\theta_D^1 - \theta_D^0}{\delta_S + \delta_D}, \tag{5}$$

$$\Delta P^* = \frac{\delta_S(\theta_D^1 - \theta_D^0)}{\delta_S + \delta_D}. \tag{6}$$

From equations 5 and 6, it is evident that $\theta_D^1 \geq \theta_D^0$ implies that $\Delta Q^* \geq 0$ and $\Delta P^* \geq 0$. Therefore, I expect the impact of subsidized pasture insurance to be positive for both quantity and price. However, the effects ΔQ^* and ΔP^* are a function of the pastureland supply slope, δ_S. To illustrate the relationship of local supply elasticities with ΔQ^* and ΔP^*, suppose supply was perfectly inelastic (i.e., vertical supply curve), such that $\delta_S \to \infty$, then I would have,

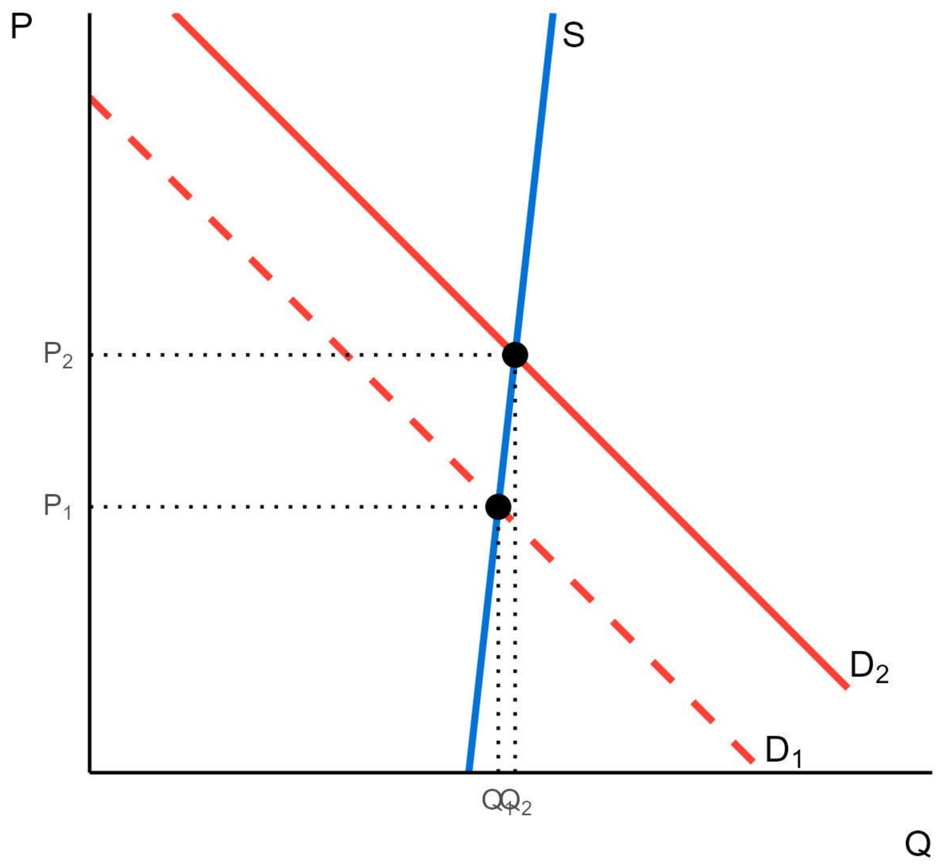
$$\lim_{\delta_S \to \infty} (\Delta Q^*) = 0, \tag{7}$$

$$\lim_{\delta_S \to \infty} (\Delta P^*) = \theta_D^1 - \theta_D^0. \tag{8}$$ [7]

Equations 7 and 8 indicate that a perfectly inelastic supply would result in no quantity change and a positive price change. For a visual illustration of relatively inelastic supply, see figure 2.2.

[7] Using L'Hôpital's rule.

Figure 2.2: Relatively Less Elastic Supply (relatively larger price response to demand shift)



In contrast, suppose supply was perfectly elastic (i.e., horizontal supply curve), such that $\delta_S \rightarrow 0$, then I would have,

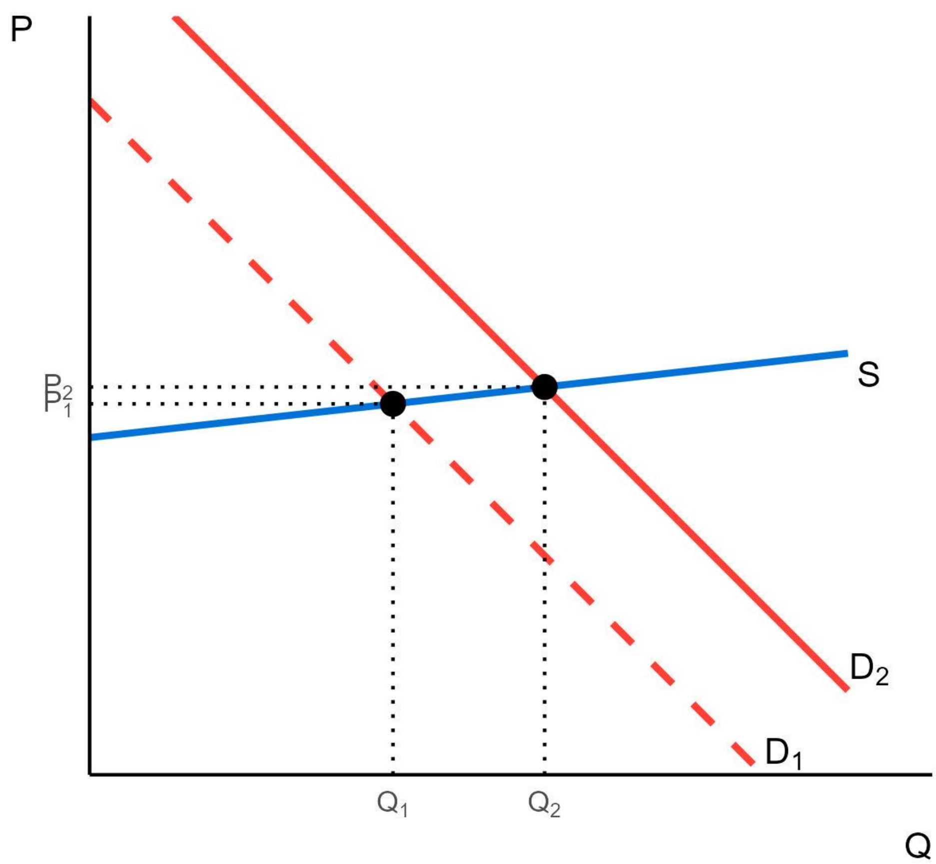
$$\lim_{\delta_S \rightarrow 0} (\Delta Q^*) = \frac{\theta_D^1 - \theta_D^0}{\delta_D}, \tag{9}$$

$$\lim_{\delta_S \rightarrow 0} (\Delta P^*) = 0. \tag{10}$$

Equations 9 and 10 indicate that perfectly elastic supply would result in a positive quantity change and no price change. For a visual illustration of relatively elastic supply, see figure 2.3.

While equations 7 through 10 illustrate the extremes of supply response, they also indicate that ΔQ^* increases with larger supply elasticities while ΔP^* decreases with larger supply elasticities.

Figure 2.3: Relatively More Elastic Supply (relatively larger quantity response to demand shift)



Since the effects of PRF insurance are a function of local supply elasticity conditions, we propose the nearby presence of public land as a possible source of heterogeneity. Public lands in the United States are frequently used for grazing livestock but are often not available for other agricultural purposes. Additionally, public lands used for grazing may often continue to be used for recreation, oil and gas permitting, or other simultaneous uses. Government agencies who oversee the land charge fees for grazing, but these fees are often relatively small (Vincent, 2012).

Thus, the marginal cost to add pastureland in counties with a large proportion of public land may be relatively low, compared to counties with large proportions of private land (which may have more alternative uses). Because supply elasticities are directly related to the marginal cost to transition land to pasture, we expect higher supply elasticities in counties with more public land, resulting in larger quantity effects and smaller price effects. Thus, public land may be a source of treatment effect heterogeneity.

In summary, my conceptual framework indicates that introduction of PRF insurance will have a positive effect on pastureland acres (quantity effect) and pastureland value (price effect), yet the effects will be heterogenous due to differences in local supply elasticities. We propose public land as a determinant of local pastureland supply elasticity, potentially altering the impact of PRF insurance on pastureland acres and value.

Empirical Framework

To identify the effects of interest in my study, we leveraged spatial and temporal variation in the staggered rollout of the PRF insurance program. This provided us with three time periods (2002, 2007, 2012); the first period consisted entirely of untreated counties, while the subsequent periods contained a group of counties where PRF insurance was available and a control group of not-yet-treated[8] counties. Importantly, the availability of PRF was an exogenous policy decision[9]. We utilized a non-traditional difference-in-differences design with variation in treatment timing, requiring a parallel trend assumption. Figures 2.4 and 2.5 validate the parallel

[8] By 2017 all counties in the continental US were eligible for PRF insurance (RMA, 2018). Therefore, we only utilized census years prior to 2017 so that each period would have non-treated observations to compare against.

[9] The exact criteria for timing and selection of counties to receive the pilot PRF program is unknown, but to the best of our knowledge it is not endogenous to the individual producers' production decisions.

trend assumption for both of my dependent variables. However, staggered treatment timing and likely heterogenous treatment effects make estimation using TWFE a concern (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). Therefore, in addition to the TWFE estimator, we also utilize the 2SDiD estimator, which is robust to the afore mentioned challenges but still relies on a parallel trend assumption (Butts & Gardner, 2021; J. Gardner, 2022).

Figure 2.4: Parallel Trends for Ln(Agricultural Land Value ($/acre))

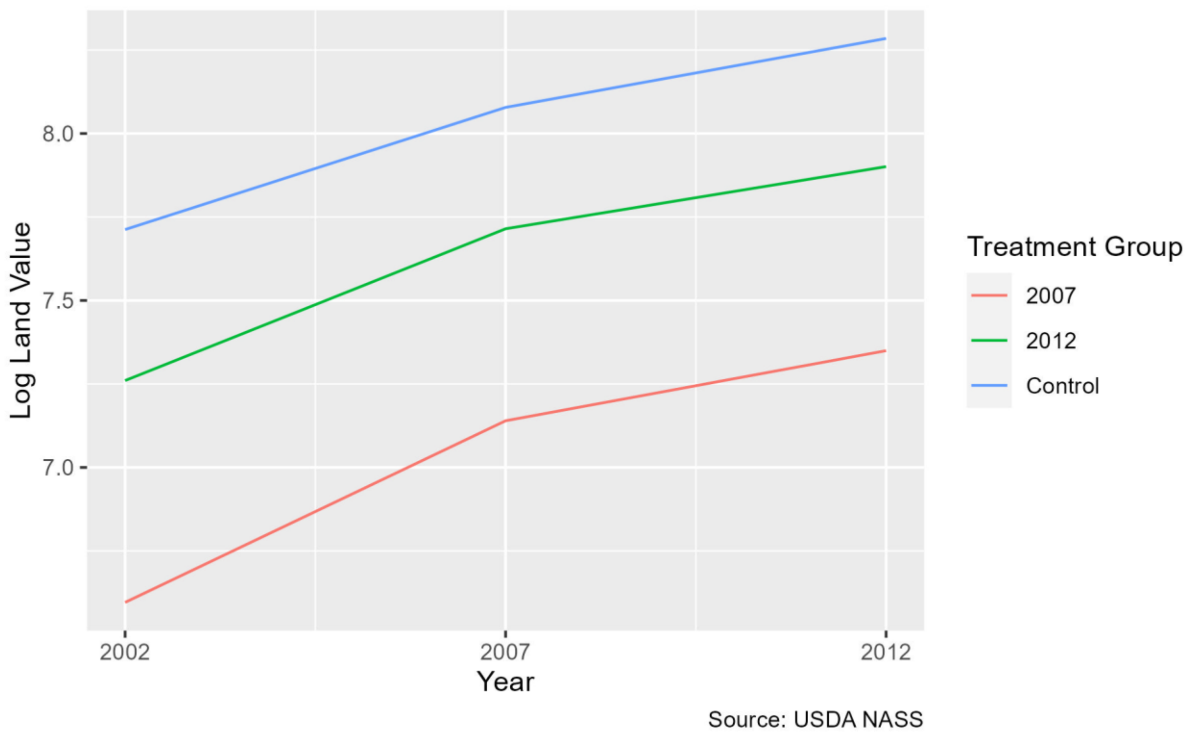
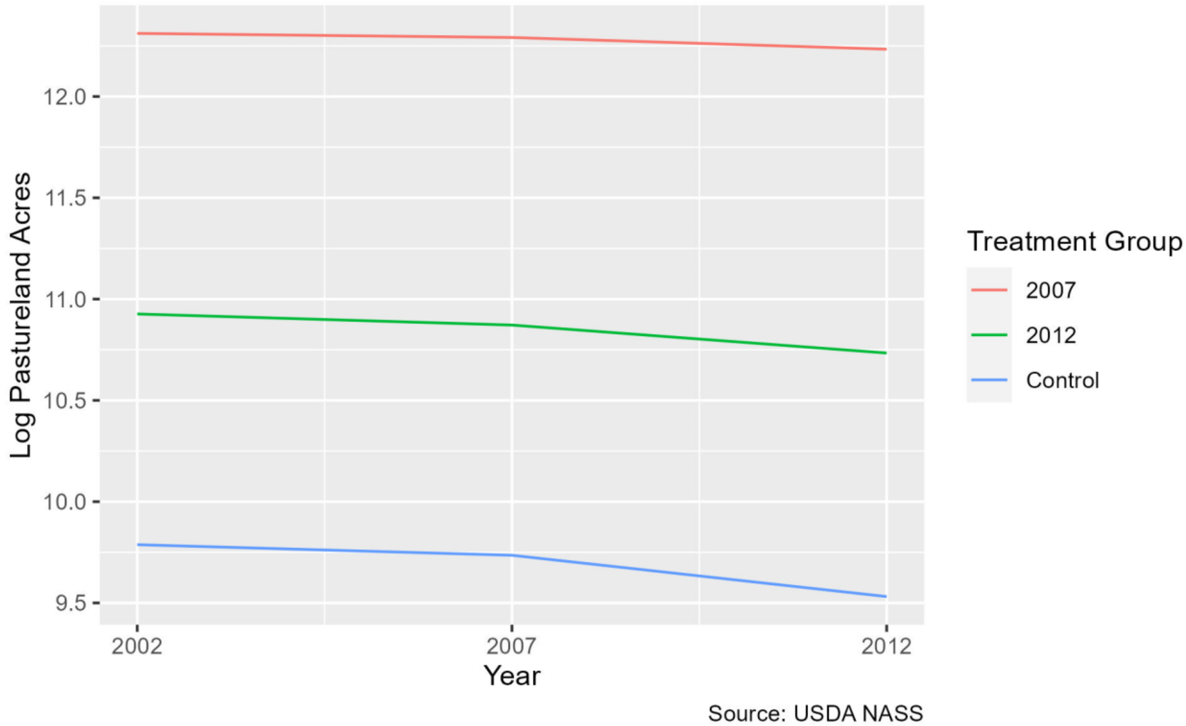


Figure 2.5: Parallel Trends for Ln(Pastureland Acres)



Two effects were estimated for each dependent variable: first, an average treatment effect (equation 11); and secondly, a heterogenous treatment effect (equation 12) with interaction effects for public land. The functional forms are,

$$\ln y_{it} = \boldsymbol{X_{it}\beta} + \tau PRF_{it} + \omega_i + \varphi_t + \varepsilon_{it}, \quad (11)$$

$$\ln y_{it} = \boldsymbol{X_{it}\beta} + \tau PRF_{it} + \lambda_2 PRF_{it}Q2_i + \lambda_3 PRF_{it}Q3_i + \lambda_4 PRF_{it}Q4_i + \omega_i + \varphi_t + \varepsilon_{it}. \quad (12)$$

Where y_{it} is the dependent variable of interest, either pastureland acres or agricultural land value for county i at time t. On the right-hand side of the equations, $\boldsymbol{X_{it}}$ is a set of county level, time variant characteristics, and β represents the associated parameters, PRF_{it} is the treatment status of county i at time t, while τ represents the average treatment effect on treated counties, ω_i is a county level fixed effect, φ_t is a period fixed effect while ε_{it} is the error for county i at time t.

Equation 12 also includes interactions between PRF_{it} and $Q2_i$, $Q3_i$, and $Q4_i$, which are a set of dummy variables indicating county i's quartile of public land percent. Lastly, λ_2, λ_3, and λ_4 are interaction effects. The marginal effects of PRF_{it}, given by $\frac{\partial y_{it}}{\partial PRF_{it}}$, were calculated when interaction effects were present. Standard errors for marginal effects were calculated via the delta method.

Data

To address my research question, we chose two dependent variables for the analysis, county level pasture acres[10] and agricultural land values (NASS, 2023b, 2023a). These were only available at the county level in 5-year increments in years when the agricultural census was conducted. Agricultural land values were chosen as a proxy for pastureland value because the latter was not available at the county level and pastureland rental rates were missing many observations. For my treatment variable we selected PRF insurance availability in a county as a binary variable (RMA, 2018). The number of public acres was used to calculate a percent of the county land area owned by the public (USGS, 2018). This percentage was further decomposed into quartiles of public land percentage, which were used as a set of dummy variables in the analysis. The public land percentage quartiles are summarized in table 2.1. While data on PRF insurance adoption rates are available, this would be endogenous because producers choose to enroll in the program (RMA, 2023). Finally, a set of variables at the county level were used as controls, including government farm payments, housing price index, unemployment, drought

[10] Does not include pasture and rangeland leased or rented on an animal unit month (AUM) or per-head basis (NASS, 2012).

conditions, precipitation, heating degree days, and cooling degree days (BLS, 2023b; FHFA, 2023; NASS, 2023c; NDMC, 2023; NOAA, 2023c, 2023b, 2023a).

Table 2.1: Public Ownership Percent Quartiles Description

	Min Public %	Max Public %	Number of Counties
Quartile 1	0%	1.18%	785
Quartile 2	1.19%	4.94%	785
Quartile 3	4.95%	17.31%	785
Quartile 4	17.32%	100%	786

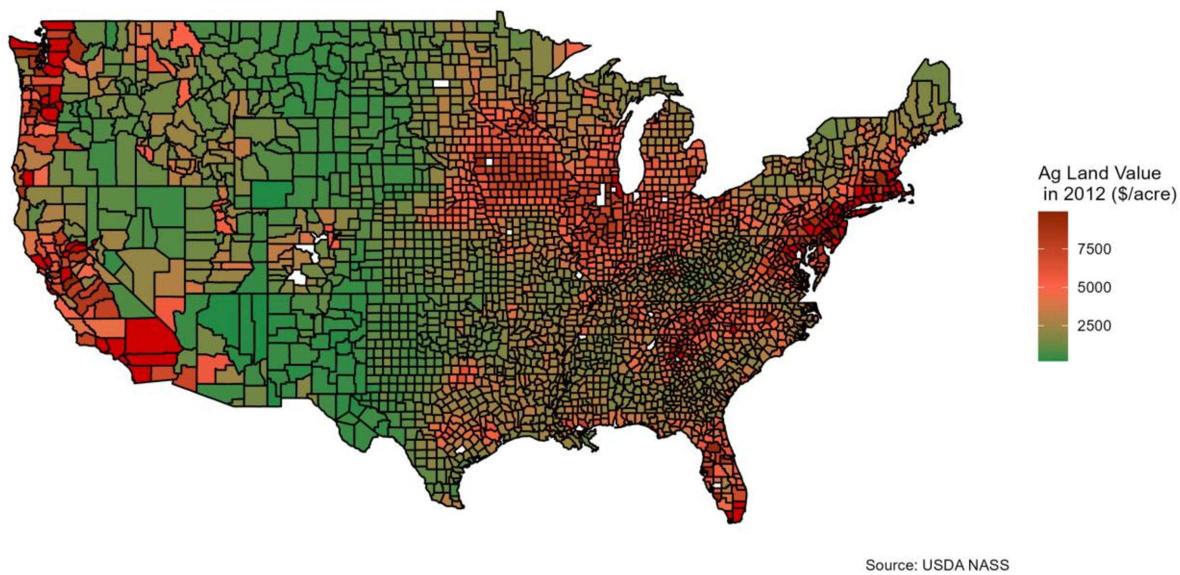
The complete dataset is a panel at the county level with observations for the years 2002, 2007, and 2012. The census year 2017 was omitted to provide ‘never-treated’ observations in the dataset as a control group. The panel data was balanced by removing counties without observations in all years, prior to estimation for each set of regressions. Balancing was not done before that because different variables had different missing observations and we sought to maximize the observations for each set of regressions. Summary statistics for the dependent, independent, and control variables are reported in table 2.2.

Table 2.2: Descriptive Statistics

PRF Availability	2007			2012			Control		
Variable	N	Mean	SD	N	Mean	SD	N	Mean	SD
Land value	981	1,520	1,172	5,154	3,295	13,745	3,030	4,085	6,830
Total pasture acres	978	385,382	356,659	5,076	178,415	387,277	3,013	31,802	72,575
Pct pasture	978	46.3	28.6	5,076	19.7	20.4	3,013	8.99	9.86
Pct public	981	14.7	22.2	5,169	16.9	23.8	3,144	8.95	13.2
Years avail	654	3.5	2.5	1,723	2.69	1.25	0		
Gov Pmts (000)	977	2,383	2,556	5,003	2,545	3,133	2,922	2,567	2,978
HPI	981	77.7	13.7	5,169	85.1	15.7	3,144	88.3	12
Pop dense	981	0.0687	0.164	5,166	0.255	2.19	3,141	0.295	0.901
Pop % chg	979	0.474	1.9	5,164	0.392	1.62	3,140	0.177	1.37
Unemp rate	981	5.55	2.47	5,169	5.93	2.55	3,144	6.7	2.31
No drought	981	37.6	32.4	5,169	41	31.4	3,144	60.4	25
d0 drought	981	62.4	32.4	5,169	59	31.4	3,144	39.6	25
d1 drought	981	42.4	33.5	5,169	40.5	33.1	3,144	21.6	22.3
d2 drought	981	26.3	28.4	5,169	25.2	28.6	3,144	10.6	17.5
d3 drought	981	13.5	20.3	5,169	12.4	20.2	3,144	4.39	10.3
d4 drought	981	3.3	8.13	5,169	3.51	9.44	3,144	0.832	4.17
Precip	981	0.524	0.24	5,169	0.689	0.285	3,144	0.901	0.228
Precip % norm	981	-5.73	19.3	5,169	-4.94	14.7	3,144	4.99	12.2
CDD	981	3.73	2.24	5,169	2.73	1.66	3,144	2.36	1.27
CDD % norm	981	25	38.9	5,169	30.2	103	3,144	19	17.1
HDD	981	8.11	4.95	5,169	9.45	4.58	3,144	9.69	3.27
HDD % norm	981	-11.3	6.62	5,169	-10.5	4.73	3,144	-10.7	3.6

The dependent variables have interesting geographic patterns, displayed in figures 2.6 and 2.7. Agricultural land values are highest on the coasts and throughout the corn belt states. On the other hand, the percent of the county used as pasture is highest along a north-south band in the western Plains states, in addition to much of New Mexico. The treatment variable is mapped in figure 2.1, where there is significant variation in treatment timing. Since the rest of the data is in 5-year increments, PRF may have been available in a treated county from 1-5 years (counting the first year as year 1). The average years since PRF availability for the dataset is 2.91. Therefore, the results should be interpreted as the treatment effect after about 3 years of treatment. Lastly, figure 2.8 maps the distribution of public land across the country. As shown in the figure, counties with the largest proportion of public land are concentrated in the western states. However, there is some overlap between counties with more public land and counties with high pasture usage rates as shown in figure 2.7.

Figure 2.6: Value of Agricultural Land in 2012 ($/acre)



Note: Land value outliers shown in cherry red.

Figure 2.7: Percent of County Used for Pasture in 2012

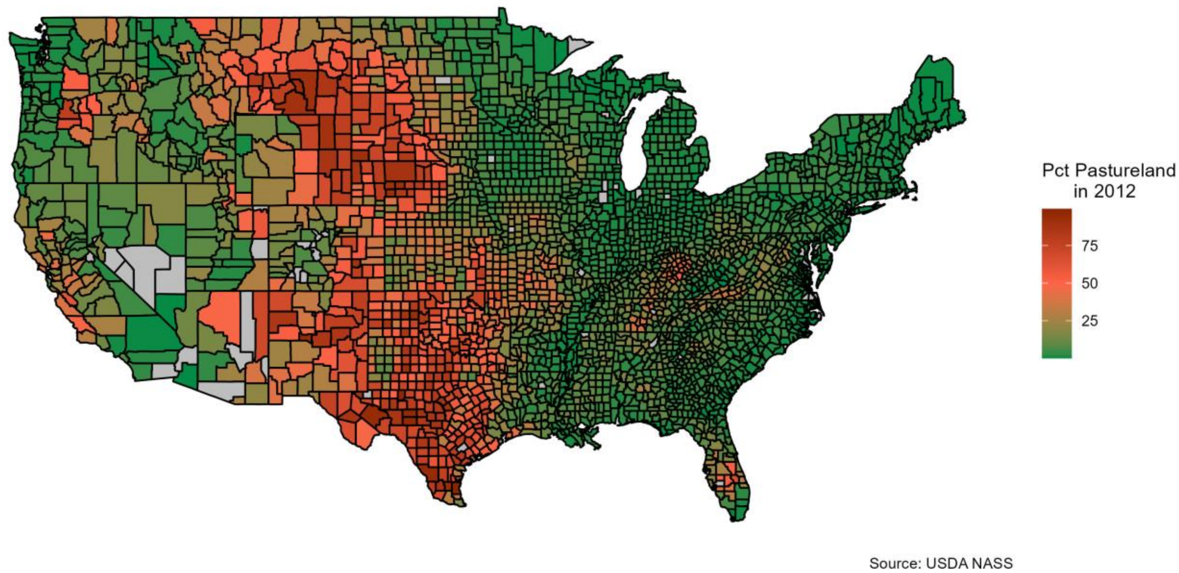
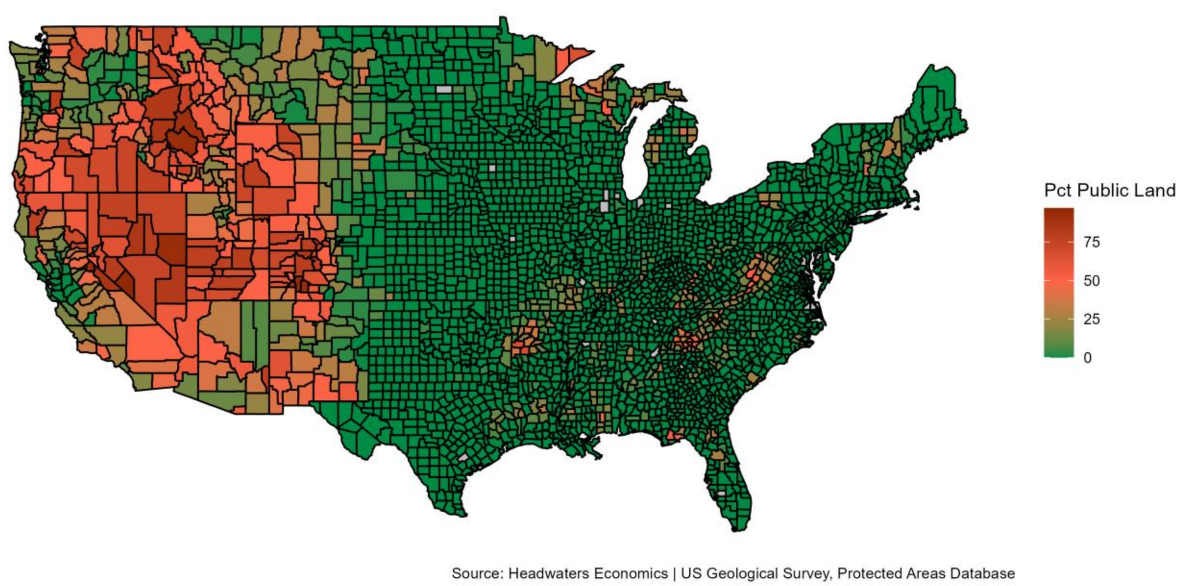


Figure 2.8: Percent of County Owned by Public



Results

The results of the empirical analysis showed that on average both pastureland acres and land values increased in response to PRF insurance availability. The results for models with pasture acres as a dependent variable are shown in table 2.3 while results for land value as the dependent variable are in table 2.4. Since the dependent variables are the natural log of y_{it}, the coefficients are interpreted as proportional effects. For pasture acres, the estimates of the average effect of PRF availability were 5.14% using TWFE and 9.57% using 2SDiD. For land value, the estimates of the average effect of PRF availability were 5.5% using TWFE and 7.59% using 2SDiD. These estimates are for an average treatment length of 2.91 years. Interestingly, in both cases the robust estimator increased the estimate of the effects when compared to the standard TWFE model.

Table 2.3: Treatment Coefficient Estimates for Pasture Acres

Estimator:	TWFE	TWFE	2SDiD	2SDiD
Dep Var:	Ln(Pasture Acres)	Ln(Pasture Acres)	Ln(Pasture Acres)	Ln(Pasture Acres)
PRF	0.0514*** (0.0080)	0.0358** (0.0124)	0.0957*** (0.0097)	0.1189*** (0.0154)
PRF x pub2		-0.0402* (0.0162)		-0.0737*** (0.0176)
PRF x pub3		0.0031 (0.0161)		-0.0432* (0.0169)
PRF x pub4		0.0905*** (0.0163)		0.0177 (0.0191)
Obs.	8,970	8,970	8,970	8,970

Notes: Each regression included the full set of control variables
Cluster robust (county level) standard errors in parenthesis.
Significance codes: p<0.01 '***'; p<0.05 '**'; p<0.10 '*'

Table 2.4: Treatment Coefficient Estimates for Land Value

Estimator:	TWFE	TWFE	2SDiD	2SDiD
Dep Var:	Ln(Land Value)	Ln(Land Value)	Ln(Land Value)	Ln(Land Value)
PRF	0.0550*** (0.0074)	0.1368*** (0.0120)	0.0759*** (0.0092)	0.1711*** (0.0164)
PRF x pub2		-0.0753*** (0.0142)		-0.1027*** (0.0172)
PRF x pub3		-0.1156*** (0.0151)		-0.1381*** (0.0186)
PRF x pub4		-0.1293*** (0.0158)		-0.1422*** (0.0207)
Obs.	9,126	9,126	9,126	9,126

Notes: Each regression included the full set of control variables
Cluster robust (county level) standard errors in parenthesis.
Significance codes: p<0.01 '***'; p<0.05 '**'; p<0.10 '*'

The effect of PRF insurance on pasture acres exhibits a pattern of decreasing before increasing in the county percent of public land. Table 2.5 contains marginal effects for each quartile of public land. The expectation was that all the public land quartile dummy interaction terms would be positive, indicating an increase in the treatment effect vs the base category of quartile 1, but this was not the case. However, public land quartile 4 has a consistently higher effect of PRF insurance on pasture acres, which matches prior expectations.

Table 2.5: Marginal Effects by Public Ownership Percent Quartiles

Estimator:	TWFE	2SDiD	TWFE	2SDiD
Dep Var:	Ln(Pasture Acres)	Ln(Pasture Acres)	Ln(Land Value)	Ln(Land Value)
Quartile 1	0.0359*** (0.0124)	0.1189*** (0.0154)	0.1368*** (0.012)	0.1711*** (0.0164)
Quartile 2	-0.0044 (0.0135)	0.0452*** (0.0151)	0.0615*** (0.011)	0.0684*** (0.0132)
Quartile 3	0.039*** (0.0126)	0.0756*** (0.0132)	0.0212* (0.0116)	0.0331** (0.0138)
Quartile 4	0.1264*** (0.013)	0.1366*** (0.0142)	0.0075 (0.0123)	0.029** (0.0138)

Notes: These marginal effects are for models with public land interactions, the 'treatment' coefficient is the marginal effect for models without interactions.
Delta method standard errors in parenthesis.
Significance codes: p<0.01 '***'; p<0.05 '**'; p<0.10 '*'

Overall, the results of my empirical analysis are mostly consistent with the conceptual model. The treatment effects of PRF are positive for both pasture acres and land value, which is the primary prediction of the theory. However, the pattern of the treatment effect on pasture acres decreasing before increasing in public land is only partially consistent with my prediction. The results do support public lands as a significant source of treatment effect heterogeneity.

Discussion

The results of my empirical analysis of the effect of PRF on land values are similar in magnitude to the results reported by Ifft et al., (2014), where the estimates ranged from 6% to 9% increase in land value. My estimates of the average effect ranged from 5.5% to 7.6% over three years depending on the estimator. The pasture acres estimates are not directly comparable to Yu et al., (2022) because their focus was on CRP enrollment, but my results are directionally consistent with theirs.

The interactions with public land quartiles showed there exists considerable geographic heterogeneity in the effects. The geographical distribution of treatment effects was mapped in figures 2.9 and 2.10. Western states are mostly in quartile 4 of public land, where we estimate increases of 13.7% in pasture acres and relatively smaller increase of 2.9% for land value in response to PRF availability. Identifying this heterogeneity provides important nuance in addition to measuring the average effects.

Figure 2.9: Estimated Marginal Effects on Farmland Value (2SDiD with public land interactions)

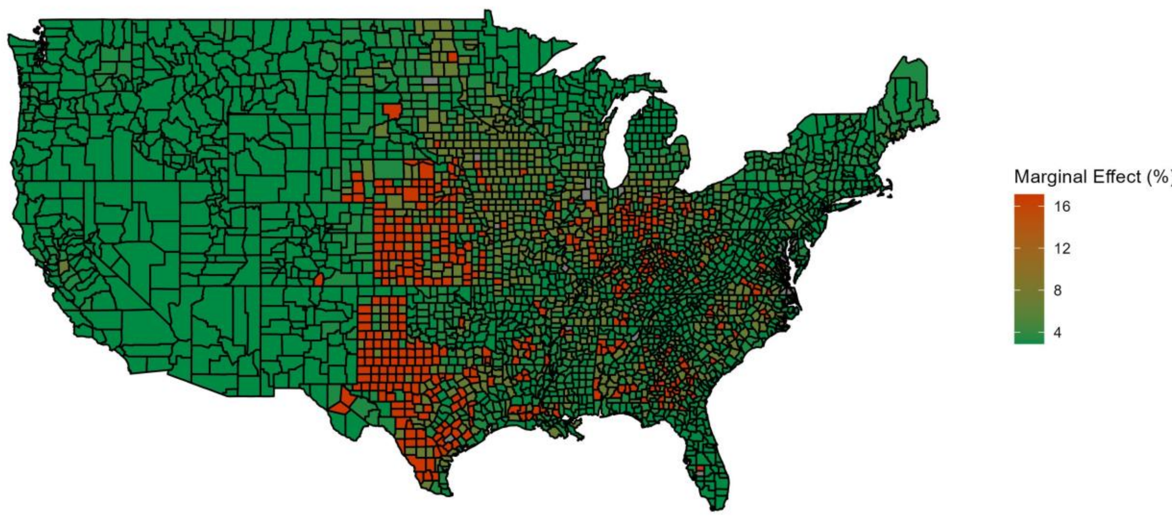
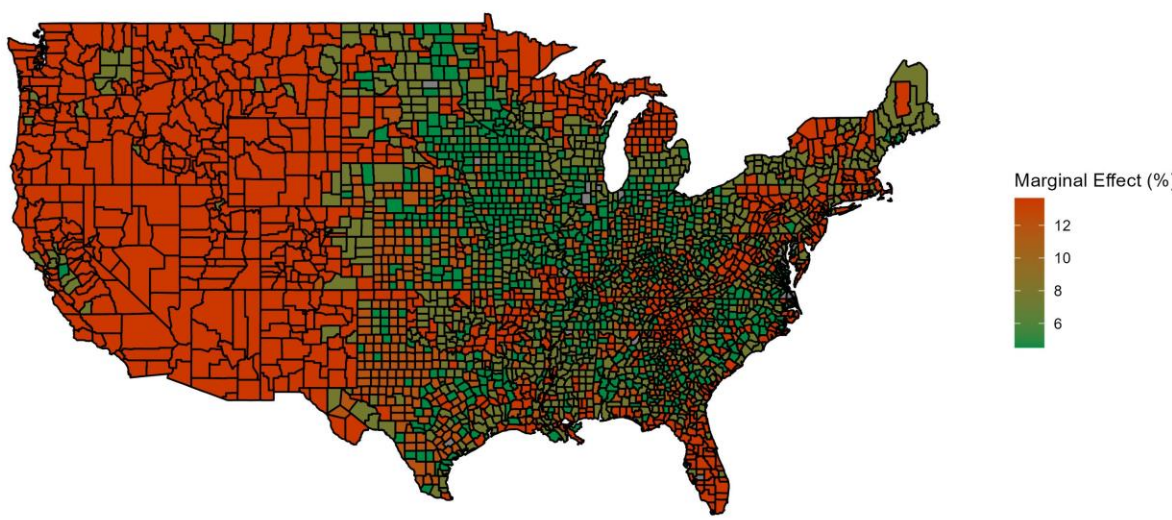


Figure 2.10: Estimated Marginal Effects on Pastureland Acres (2SDiD with public land interactions)



This study is unique because it approached the effects of the PRF insurance program from both a price and quantity perspective. Previous work analyzing this program has either focused on land value effects or land use effects, not both. Furthermore, we identify a source of heterogeneity in the effects which has distinct regional patterns. This gives some insight into the spatial distribution of the effects of interest.

The data used in the empirical assessment was imperfect in several ways. First, more frequent observations would have yielded increased statistical power and better insight on impact timing. However, several variables were only available in agricultural census years. Secondly, we were unable to obtain a direct measure of pastureland value, so the broader agricultural land value was used. This is an imperfect proxy, yet the results are likely conservative estimates. In summary the data was imperfect but adequate to answer the research question.

Summary & Conclusion

In this study, we examined the impact of PRF insurance on farmland values and pastureland area. We utilized the staggered rollout of PRF at the county level in a non-traditional Difference-in-Differences framework and found a positive average effect on both farmland value and acres of pastureland. Higher percentages of public land in a county are associated with smaller effects on land value and larger effects on pasture area. My results are in line with previous research but provide additional details on the geographic heterogeneity of effects. This additional nuance gives policy makers insight into the distribution of PRF program effects across the country.

Future work could investigate more deeply sources of effect heterogeneity, look at livestock supply impacts, or discover the prior uses of additional pastureland drawn in by the PRF program. Additionally, this study reports estimates of quantity and price impacts separately, an extension could estimate these impacts together in a system. Further, the estimates of price and quantity impacts could be used as inputs to analyze the economic welfare impact of PRF insurance.

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