JOURNAL of FOOD DISTRIBUTION RESEARCH

Volume 56 / Issue 1 / March 2025

Published by

FDRS
FOOD DISTRIBUTION RESEARCH SOCIETY

http://www.fdrsinc.org

Food Distribution Research Society

2025 Officers and Directors

Journal of Food Distribution Research
Volume 56, Issue 1
March 2025

ISSN 0047-245X

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Food Distribution
Research Society

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Food Manufacturers' Decision Making Under Varying State Regulation

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Abstract

States are increasingly regulating the production practices, ingredients, and labeling of food products sold within their borders. This patchwork approach to food policy is likely to have significant ramifications for the U.S. food sector and interstate agri-food trade. We develop a conceptual framework to assess how differences in states' regulations influence food manufacturers' costs and production decisions. Using the model, we examine differences in producer behavior across three policy examples, illustrating how firms respond to regulatory costs and highlighting the implications of interstate heterogeneity in food policy.

Keywords: state regulation, food policy, food manufacturing, federalism, interstate trade

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Introduction

Debate over the proper role of federal and state governments is as old as the nation. In the area of food policy, oversight was primarily entrusted to individual states until the early 1900s, when interstate commerce accelerated and food production issues moved to a national scale (Fortin, 2009). The federal government took charge over many aspects by establishing the regulatory system that exists today. Today, as the federal government plays a prominent role in regulating the agri-food sector through the work of federal agencies, including the Food and Drug Administration (FDA), the U.S. Department of Agriculture (USDA), and others, the role of states can become obscured. However, the principle of federalism—the rights and responsibilities of individual states to enact and enforce policy—ensures that state-level regulation remains a critical aspect of U.S. food policy (Foote, 1984). States' roles in regulating the food system occupies an increasingly prominent position in the U.S. regulatory environment (Sutton, 2024).[1] This patchwork approach to food policy has created a complex environment, requiring firms along the food supply chain to adapt to evolving and disparate regulations. Ultimately, these developments are likely to have significant ramifications for firms, consumers, and interstate trade in agri-food products.

A recent illustrative example can be found in California's Assembly Bill 418 (AB-418), passed in November 2023 and which by 2027 will ban the sale of food products that contain any of four additives identified by the law as harmful to human health. Specifically, the law bans the sale of products with brominated vegetable oil (BVO; an emulsifier used in soft drinks), potassium bromate (an improving agent for flour used to strengthen dough), propylparaben (a preservative), and Red Dye No. 3 (a coloring agent). Following the law's passage, lawmakers in several other states, including New York, Illinois, and Pennsylvania, followed suit in advancing similar regulations (Bottemiller Evich, 2024; Henderson, 2024). While the content of other states' proposed laws broadly aligns with California's, the new regulations reflect critical differences. For instance, Pennsylvania's proposed rules would ban an assortment of food coloring agents not targeted by other states' rules, and New York's proposal would outlaw several ingredients not covered by California's law. The proposed rules also reflect differences in which products would be exempt from the regulation, timelines for compliance, enforcement mechanisms, and penalties for noncompliance. At the time of the law's passage, the use of these additives remained mostly unrestricted at the national level and in many other states. Consequently, food manufacturers that use the soon-to-be-banned ingredients will need to respond to markedly different regulations across the states in which they sell their products.

Other instances abound of an individual state's regulation exerting significant influence on the food system. Prominent examples include Vermont's 2014 mandatory labeling law for genetically modified (GM) ingredients and California's 2018 law regulating animal welfare standards (Proposition 12). In both instances, food manufacturers who sold their products across multiple states or the entire country were obliged to react to a regulatory change in a single state. The passage of food laws at the state level has also become an increasingly politically charged issue,

[1] Likely to accelerate this patchwork approach to regulation is the U.S. Supreme Court decision in June 2024, which ended the so-called "Chevron Defense," thereby limiting the power of federal regulatory agencies.

as many laws are now seen as a precursor for the creation of national food regulations, driven by both increased salience and lobbying.

Following California's recent food additive law, for example, advocacy groups across the food system released statements either approving of or opposing the new law. The Environmental Working Group, a nonprofit advocacy group that focuses on policy issues affecting agriculture and the environment, noted that, "In the absence of federal action, states have stepped up to protect their consumers" (EWG, 2024). A representative from the National Confectioners Association (whose members are likely to be affected by the law) stated, "It's time for FDA Commissioner to wake up and get in the game. These activists are dismantling our national food safety system state by state in an emotionally driven campaign that lacks scientific backing" (Bottemiller Evich, 2024). Former FDA Deputy Commissioner Frank Yiannas opined that, while the law was well-intentioned, it set a "dangerous precedent" on how food safety standards are set (Yiannas, 2023). The FDA, for its part, reasserted its safety review process and then months later restricted the use of two of the additives restricted in the California law, first BVO in July 2024 and then Red Dye No. 3 in January 2025.

While these issues have grown in salience for both researchers and policy makers, remarkably little has yet been done to systematically assess the ways in which federalism in food policy shapes the decisions of firms in the food supply chain and to characterize the costs associated with this regulatory heterogeneity. The broader ramifications of this trend in policymaking for the U.S. food sector thus remain an open question.

To address this gap, in this paper we analyze food manufacturers' decision making under varying state regulations. To do this, we first provide an overview of the institutional background and survey of the existing literature on federalism in U.S. food policy. We next develop a conceptual framework that allows us to characterize the margins along which firms respond to differences in food policy across states. We then evaluate three policy examples—Vermont's GM labeling law, Illinois' sesame allergen labeling law, and California's food additive law—to illustrate the real-world responses of firms to heterogeneity in interstate regulation. Finally, we conclude by synthesizing the key takeaways of our analysis and offering policy recommendations toward maximizing the economic efficiency of the regulatory environment facing the U.S. food system. Taken together, the components of our analysis shed light on the increasingly important issue of federalism in U.S. food policy.

Institutional Context

Federalism in U.S. food policy is governed by a set of fundamental principles enshrined in the Constitution. The Constitution provides states with so-called "police power," allowing them to establish and enforce rules to protect the health and welfare of their people, an objective intrinsically related to food policy. Importantly, the Constitution also endows the federal government with two core powers that limit the scope of states' regulatory efforts: (i) the Supremacy Clause, which establishes that federal laws should take precedence over state laws when the two are in conflict, and (ii) the Commerce Clause, which assigns responsibility for the regulation of interstate commerce to the federal government. Today, with authority over many aspects of food regulation in the hands of the federal government, it is easy to lose sight of the fact that states can—and do—regulate the production and sale of food within their borders.

Courts have continued to uphold states' rights to regulate food produced or sold in their state, so long as such regulations are not inconsistent with federal law and do not unduly burden interstate commerce or discriminate against out-of-state producers (Foote, 1984; 1985; Fortin, 2009; McCabe, 2010). Fortin (2009) notes, "Accordingly, firms shipping into various states must be careful that they meet both federal and state requirements."

Literature Review

The literature evaluating the economic impacts of federalism's role in food policy remains nascent, and only a small number of existing studies directly analyze how firms respond to patchwork food regulation. An important example is work that investigates the case of California's 2010 law (AB-1437), requiring that all eggs sold in the state be produced using cage-free production methods by 2015. This research has documented that AB-1437 increased the price of eggs sold both within and outside of the state, the volume of California's imports of eggs from other states, and the proportion of cage-free production in the overall supply of eggs (Allender and Richards, 2010; Malone and Lusk, 2016; Carter, Schaefer, and Scheitrum, 2020; Oh and Vukina, 2021).

Though most work in this area does not focus directly on food manufacturers' decision making, this literature finds evidence of differing responses of firms to changes in regulation. For example, Carter, Schaefer, and Scheitrum (2020) find that some egg producers began selling and some stopped selling to the California market following the law's enactment, with larger firms being more likely to exit and smaller firms being more likely to enter the state. Additionally, Allender and Richards (2010) note that some firms sold both cage-free and conventional egg products prior to the state law, and thus faced different constraints in complying with the law relative to firms that initially produced only one or the other variety. It is likely that the specific context of this case—the large size of California's market for eggs, consumer preferences surrounding the cage-free attribute, and the likelihood of federal involvement—was key in shaping firms' responses.

Most closely related to our analysis is the work of Caswell and Kleinschmit (1997), who developed a conceptual framework for assessing the costs and benefits associated with state food policy. They base their analysis on the specific case of a 1986 Massachusetts law establishing a maximum residue limit (MRL) for the plant growth regulator, Alar, used in the processing of apples. Critically, Massachusetts' rules for Alar were more conservative than federal limits established by the Environmental Protection Agency (EPA), thus binding the sale of apples in Massachusetts to a stricter standard than that maintained at the national level. Caswell and Kleinschmit delineate the different actions that a food manufacturer might pursue in response to the regulation. They specifically outline four possible responses: one in which the firm sells a single Alar-free product nationwide and three other strategies in which the firm produces two distinct products (an Alar-free version for Massachusetts and a conventional version for other states). The three cases captured by the two-product option differ based on the three potential pricing responses for Alar-free products faced by the firm: no price premium, partial price premium, and full price premium. In the conceptual analysis that we develop below, we extend Caswell and Kleinschmit's theoretical framework to a more general setting to analyze producers' responses to regulatory heterogeneity across different markets.[2]

The limited existing literature evaluating the impact of varying state food regulation has generally focused on laws that restrict the sale of food items produced using a particular agricultural practice. However, many recent state laws relate to the ingredients used in a food product or its packaging; in most of these cases, the prohibited ingredients remain largely unaffected by other states' regulations. These laws are likely to affect various decision makers (e.g., farmers versus food manufacturers versus retailers) in different ways and impose disparate costs on different actors in the supply chain. Food manufacturers often produce many products—each with many ingredients—and sell to distributors and retailers in most or all states. Research that estimates the costs of complying with federal bans or labeling of ingredients has found that these changes can impose a substantial cost on impacted firms (Muth et al., 2015a; Muth et al., 2015b), and results from focus groups with food manufacturers found that regulation was the concern most frequently raised by participants (Adelaja et al., 1997).

Finally, and despite our focus on the domestic policy setting, it is worth highlighting the analogous issue of regulatory heterogeneity in the international trade context. The fragmented approach to food policy as pursued by individual states offers close parallels with the application of non-tariff measures (NTMs), such as sanitary and phytosanitary standards and technical barriers to trade. In essence, many states' regulations toward the food system are themselves NTMs but in the setting of domestic trade. Considering the international policy context is thus informative about the likely effects of state-level regulations that impact interstate trade in agri-food products.

Though many NTMs are likely to be trade-inhibiting owing to both the costs that they impose on producers and exporters and their contributing to a more opaque trade policy environment (Fernandes, Ferro, and Wilson, 2019), the literature has nonetheless established that NTMs can yield either trade-reducing or trade-enhancing impacts (Santeramo and Lamonaca, 2019). While the explanation for the former relationship is intuitive, the origins of the latter could relate, for instance, to trade-expanding effects from bolstered consumer confidence due to more rigorous health and safety rules (Liu and Yue, 2012), decreased production and trade costs originating from

[2] Several critical factors differentiate our modeling framework from that of Caswell and Kleinschmit (1997) (hereafter, C&K). First, our conceptual environment more strongly emphasizes firms' decisions along the extensive margin (i.e., decisions pertaining to which markets to serve and which versions of products to sell). By contrast, the primary focus of C&K is on the price responses faced by firms following regulatory changes (though C&K do consider the possibility of firms selling different versions of products in different markets). Second, our modeling approach analyzes changes in both fixed and variable costs arising from regulatory changes, another point that distinguishes our framework from that of C&K. Accounting for these two distinct types of costs has important implications for firm behavior relating to which markets to serve and the mode by which to serve them. Third, our conceptual framework considers consumer demand in a more flexible way than C&K. Whereas their analysis assumes that reformulated products (in their context, products adhering to stricter MRLs) are generally more preferred by consumers, we account for the possibility that new versions of products could either be more or less preferred by consumers to the original version, both of which outcomes have been observed in different real-world scenarios.

the harmonization of regulatory standards across markets (Ridley, Luckstead, and Devadoss, 2024), or reductions in information asymmetries (Xiong and Beghin, 2014).[3] Whatever effects the wide array of NTMs may have can vary widely across products, locales, and regulatory settings, which can make it difficult to draw systematic conclusions about how NTMs, and interjurisdictional heterogeneity in food policy more generally, ultimately affect producers, consumers, trade, and the welfare of market participants. Similar ambiguity in these effects is likely to characterize the impacts arising from the often-patchwork approach to U.S. interstate food policy.

Conceptual Framework

To formally characterize the economic factors that influence the reactions of food manufacturers to changes in state regulation, we develop a conceptual framework with which to analyze the various margins along which producers respond to differences in regulation in food manufacturing across states. By accounting for the various costs and benefits associated with different responses by firms to changes in regulation, this framework allows us to establish empirical predictions on firms' decision making that will inform our case study analysis detailed in the next section.

Consider a representative, profit-maximizing firm that, prior to any changes in regulation, sells product x in states A and B.[4] Production of x uses a specific ingredient that initially faces no restrictions on its use. We suppose that state A enacts a new regulation restricting the acceptable uses of the ingredient. In line with the real-world examples outlined above, such regulations might include a complete ban on the use of the ingredient, labeling requirements for products that contain the ingredient, or limits on the allowable levels of the ingredient contained in products. We focus on the case of a state-level ban on the ingredient's use, though our analysis also captures the key features of the other regulatory cases.

In response to the regulation, the firm can continue to produce the original formulation of x, which contains the banned ingredient and/or develop a reformulated version of the product, denoted as $\tilde{x}$, which contains a substitute ingredient not subject to the ban.[5] Consequently, the firm must choose which version of the product to sell (or not) in each state based on the relative profitability of different possible responses to the change in regulation.

Production takes place under a constant-returns-to-scale technology with variable and marginal costs that can differ between the two versions of the product (denoted as c_i for $i = x, \tilde{x}$). Depending on which version of the product the firm sells in a given market, the firm faces linear inverse demand $p_{i,j} = a_{i,j} - b_{i,j}q_{i,j}$, where $p_{i,j}$ is the price of product i in market j and $q_{i,j}$ is the

[3] Xiong and Beghin (2014) specifically analyze the effects of MRLs in internationally traded plant products. The consideration of MRLs in the context of international trade shares clear parallels with the domestic market impacts analyzed by Caswell and Kleinschmit (1997) in the case of Massachusetts' MRLs for Alar in apples.
[4] The logic of our analysis readily extends to cases of more than two states/markets.
[5] In the case of ingredient labeling requirements, $\tilde{x}$ can also be interpreted as the relabeled version of the product.

quantity purchased by consumers.[6,7] The parameters $a_{i,j}, b_{i,j} > 0$ reflect consumer preferences, with the demand shifter $a_{i,j}$ reflecting differences in consumer preferences for the two versions of the product across markets as well as differences in the sizes of the respective markets.

These relationships yield equilibrium pre-regulation profits (Π^0) for the firm equal to

$$\Pi^0 = \underbrace{(p_{x,A} - c_x)q_{x,A}}_{\pi_{x,A}} + \underbrace{(p_{x,B} - c_x)q_{x,B}}_{\pi_{x,B}}, \tag{1}$$

where $\pi_{x,A}$ and $\pi_{x,B}$ denote variable profits (i.e., producer surplus) received by the firm from selling product x in states A and B, respectively.[8] We assume that the firm can respond to the new regulation in one of four ways (see Figure 1):

> **Option 1 (reformulate and separate production):** Switch to producing the regulation-compliant product ($\tilde{x}$) for the regulating state (A) while maintaining separate production of the original (noncompliant) version of the product (x) for the non-regulating state (B). To reformulate production from x to $\tilde{x}$, the firm must incur a fixed cost (denoted f_R). Establishing separate production lines for the new (compliant) and old (noncompliant) versions of the product imposes an additional fixed cost on the firm (denoted f_S).[9,10]

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[6] We assume that the markets of states A and B are sufficiently separated such that spatial arbitrage does not occur. Thus, the firm charges different prices in both markets. Additionally, and for tractability, we consider the firm's actions in terms of corner solutions (i.e., we assume that the firm only sells a single version of a product (x or $\tilde{x}$) in a given state's market). Based on our conversations with food industry representatives, such an assumption is consistent with the observed behavior of most food manufacturers.

[7] Our framework is intentionally agnostic on price effects and allows for impacts on prices to be flexibly realized through changes in firms' variable profits. There are two principal reasons for this. First, we do not impose explicit assumptions on market structure with which to solve for equilibrium prices. Because our objective is to analyze the behavior of firms in response to regulatory changes under a variety of settings, this decision is made to ensure the generality of the results. Second, our model does not take a definitive stand on how the various firm responses that we delineate affect either producers' variable costs or consumer demand. This is because, as evidence from the literature shows, different responses by firms to regulatory changes could either increase or decrease producers' variable costs and could likewise have either positive or negative impacts on consumer demand (see, e.g., Carter and Schaefer [2018] on impacts on input prices or Fan, Stevens, and Thomas [2022] on demand impacts, both relating to Vermont's GM labeling law). Because such impacts are ambiguous, we refrain from drawing any categorical conclusions about price effects.

[8] The Appendix provides the full description of the model's equilibrium.

[9] In reality, it is probable that the costs of product reformulation or separation are themselves a function of a firm's size. Though we treat these costs as independent of the firm's output levels ($q_{i,j}$), our framework nonetheless captures this aspect of real-world costs—larger firms would simply face a larger value of f_R or f_S.

[10] Previous literature has examined some of these costs, including the costs of both compliance and separation. Regarding compliance, the FDA has created a tool to estimate the cost of complying with national regulation via reformulation (Muth et al., 2015a) and relabeling (Muth et al., 2015b). We would expect the costs of complying with state-level regulation to be similar, with the caveat that states often require shorter timelines for compliance, which can substantially increase the associated costs. Similarly, maintaining separate versions of a product in both production and transportation can be expensive. For example, research has highlighted the high costs associated with segregation of GM and non-GM food products (Alston and Sumner, 2012; Lesser, 2014; Bovay and Alston, 2018).

Option 2 (reformulate for both markets): Switch to producing only the reformulated, regulation-compliant product for sale in both states. In this case, the only fixed cost incurred by the firm is the cost of reformulation (f_R).

Option 3 (exit the regulating market): Discontinue all sales of the product in the regulating state, while continuing to sell the original version of the product in the non-regulating state. The firm thus incurs no costs from reformulation, separation, or potential legal penalties, but foregoes all profits that would have been earned from sales in state A.

Option 4 (ignore the regulation): Sell the original, non-reformulated version of the product in both states at the risk of being subject to penalties and/or litigation due to noncompliance. In ignoring or imperfectly complying with the regulation and continuing to sell the original version of the product in state A, the firm runs the risk of incurring costly legal penalties (f_L) with probability θ. Penalties can range from fines to allowing for civil cases to be brought against offenders by either lawmakers or private citizens.

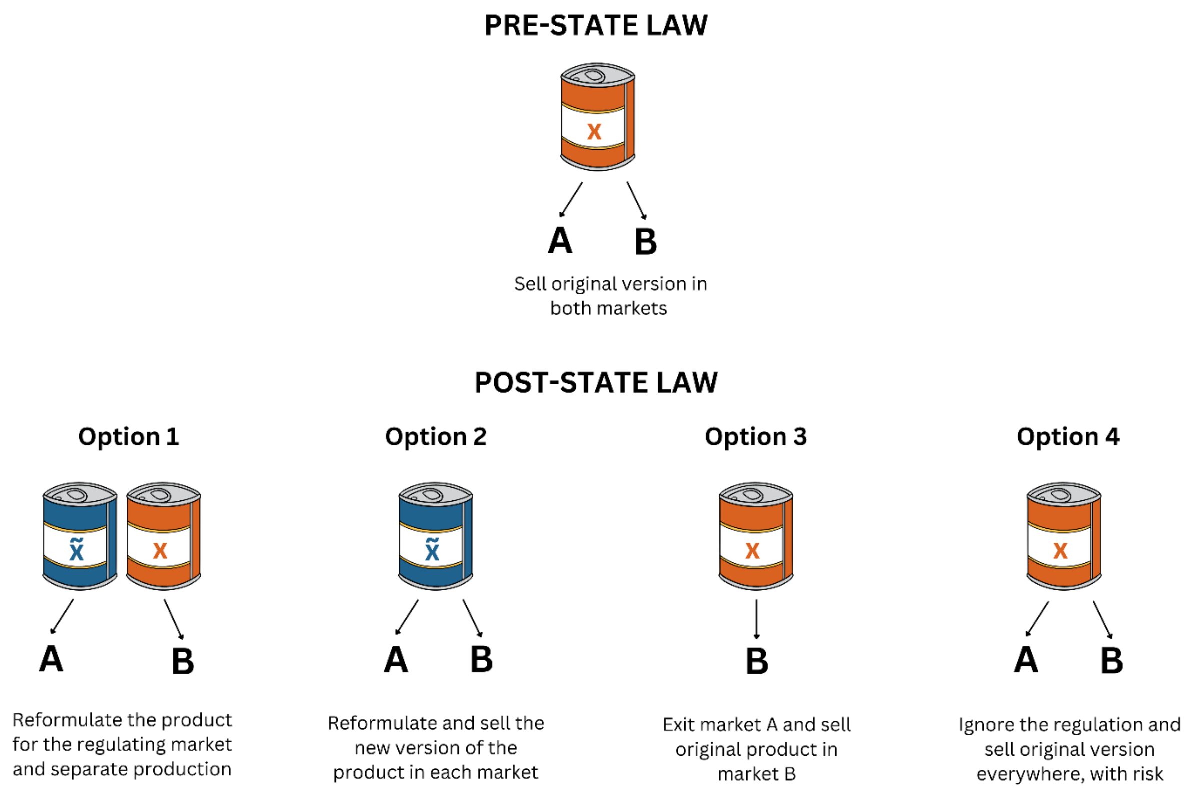

Figure 1. Possible Firm Responses to New Regulation in State A

On the demand side, the ultimate effect of reformulation depends on consumer preferences. If the reformulated product is preferred to the original product the effect is positive, if the reformulated product is less preferred it is negative, and if consumers are indifferent between them the effect is zero. Variable profits from selling the reformulated version of the product are thus denoted by $\pi_{\tilde{x},A}$

and $\pi_{\tilde{x},B}$ for states A and B, respectively, which are characterized by expressions analogous to their counterparts for $\pi_{x,A}$ and $\pi_{x,B}$ defined above. Based on this, we define $\Delta\pi_A = \pi_{\tilde{x},A} - \pi_{x,A}$ and $\Delta\pi_B = \pi_{\tilde{x},B} - \pi_{x,B}$ as the change in the firm's variable profits in states A and B, respectively, from selling the reformulated version of the product in the each market.

Following the implementation of state A's regulation, the firm's expected profits depend on which option the firm chooses in response. The profits earned by the firm in each case (with Π^k denoting profits under options $k = 1, \dots, 4$) are given as follows:

Option 1 (reformulate and separate production)

$$\Pi^1 = \pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S \tag{2}$$

Option 2 (reformulate for both markets)

$$\Pi^2 = \pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R \tag{3}$$

Option 3 (exit the regulating market)

$$\Pi^3 = \pi_{x,B} \tag{4}$$

Option 4 (ignore the regulation)

$$\Pi^4 = \pi_{x,A} + \pi_{x,B} - \theta f_L \tag{5}$$

Based on these expressions, the firm's optimal response to the regulation can be analyzed in relation to the model's key elements, including differences in consumer tastes for the two versions of the product, the size of the costs of reformulating or separating production or legal penalties, changes in variable costs of production, and other factors. Below we summarize the key takeaways obtained from considering the firm's profit-maximizing decisions under the four options. Firms will optimally choose each option under the following conditions.[11]

Option 1:

$$\Pi^1 > \Pi^2 \colon -f_S > \Delta\pi_{x,B} \tag{6a}$$

$$\Pi^1 > \Pi^3 \colon \pi_{\tilde{x},A} - f_R - f_S > 0 \tag{6b}$$

$$\Pi^1 > \Pi^4 \colon \Delta\pi_A - f_R - f_S > -\theta f_L \tag{6c}$$

Equation (6a) describes that the firm will optimally reformulate the product for the regulating market and maintain separate production when the fixed cost of separation ($-f_S$) is less negative than the change in net profits from separating production and selling the original product in state B ($\Delta\pi_{x,B}$). If the firm's variable profits would decline due to selling the reformulated product in

[11] See the Appendix for the derivation of profits for each of the pairwise comparisons.

state B ($\Delta\pi_{x,B} < 0$), either because of decreased revenues, increased variable costs, or both, then the firm's expected loss in variable profits in state B would need to exceed the fixed cost of separation for this condition to hold. If the firm's variable profits strictly increase from selling the reformulated product in state B ($\Delta\pi_{x,B} > 0$), then this condition will never hold, and the firm would never optimally separate production. Intuitively, if separation costs are low, consumers strongly prefer the original version (revenues from selling version x are higher than from selling version $\tilde{x}$), and/or variable costs for the reformulated product are comparatively high ($c_{\tilde{x}}$ is higher than c_x), the firm will be more willing to bear the cost of reformulation and separation, all else equal. Equation (6b) indicates that the firm will optimally separate production over exiting the regulating market when the net total profits from selling the reformulated version of the product in state A ($\pi_{\tilde{x},A} - f_R - f_S$) are positive. Finally, equation (6c) describes that the firm will optimally separate production over flouting the regulation when the net change in total profits from reformulating for state A's market and selling the original version of the product in state B ($\Delta\pi_A - f_R - f_S$) outweigh the expected legal penalties from violations of the regulation ($-\theta f_L$). This will occur under the prospect of larger penalties (higher f_L) and/or more active enforcement (higher θ), both of which incentivize firms to more readily comply with the regulation.

Option 2:

$$\Pi^2 > \Pi^1 \colon \Delta\pi_{x,B} > -f_S \tag{7a}$$

$$\Pi^2 > \Pi^3 \colon \pi_{\tilde{x},A} + \Delta\pi_B - f_R > 0 \tag{7b}$$

$$\Pi^2 > \Pi^4 \colon \Delta\pi_A + \Delta\pi_B - f_R > -\theta f_L \tag{7c}$$

Equation (7a) reflects the inverse logic of equation (6a), in that firms will pursue Option 2 over Option 1 when the change in variable profits from selling the reformulated product in the non-regulating state is greater than the cost of separating production (i.e., $\Delta\pi_{x,B}$ is greater than $-f_S$). Equation (7b) depicts that the firm will optimally choose Option 2 over Option 3 when the variable profits earned in state A and the change in variable profits in state B minus the fixed cost of reformulation are positive; in essence, this condition describes that it will generally be more profitable to uniformly reformulate the product rather than exit the regulating market when the firm's profits in the regulating market are large ($\pi_{\tilde{x},A}$), the firm expects to earn higher variable profits or undergo only a small decrease in variable profits after reformulating for state B ($\Delta\pi_B$ is positive, or is negative and small), and/or if the costs of reformulation ($-f_R$) are small. Finally, equation (7c) shows that the firm will reformulate production for both markets when the changes in net profits across markets from selling the reformulated product outweigh the expected legal penalties from noncompliance (i.e., $\Delta\pi_A + \Delta\pi_B - f_R$ is greater than $-\theta f_L$). This occurs in instances where reformulation does not cause large negative changes in total variable profits (either through the revenue or variable cost components of $\Delta\pi_A$ and $\Delta\pi_B$), costs of reformulation are high, or the probability of regulatory enforcement and/or the size of legal penalties are small.

Option 3:

$$\Pi^3 > \Pi^1: 0 > \pi_{\tilde{x},A} - f_R - f_S \tag{8a}$$

$$\Pi^3 > \Pi^2: 0 > \pi_{\tilde{x},A} + \Delta\pi_B - f_R \tag{8b}$$

$$\Pi^3 > \Pi^4: 0 > \pi_{x,A} - \theta f_L \tag{8c}$$

Equations (8a) and (8b) reflect the inverse of the cases captured by equations (6b) and (7b). Equation (8d) describes the conditions under which the firm would optimally exit the regulating market over not complying with the regulation: firms will pursue this option in instances where profits in the regulating state ($\pi_{\tilde{x},A}$) are small (i.e., when lost sales from exiting rather than reformulating would be small) relative to the cost of potential legal penalties from noncompliance with the regulation.

Option 4:

$$\Pi^4 > \Pi^1: -\theta f_L > \Delta\pi_A - f_R - f_S \tag{9a}$$

$$\Pi^4 > \Pi^2: -\theta f_L > \Delta\pi_A + \Delta\pi_B - f_R \tag{9b}$$

$$\Pi^4 > \Pi^3: \pi_{x,A} - \theta f_L > 0 \tag{9c}$$

Because each of the comparisons portrayed in equations (9a) through (9c) were elaborated in the preceding equations, for brevity, we omit discussion of these relationships.

Before proceeding, it is important to underscore that our analysis considers a setting with only two states with only a single difference in regulation. In reality, regulatory differences are likely to create a significantly more complex policy environment than the one we consider, especially in instances where states pass similar (but not identical) laws. As the number of states with disparate regulatory environments increases, many of the costs in our framework (e.g., compliance, separation, lost sales in regulating states) would be likely to increase alongside.

Expected Firms' Decisions Under the State Regulations

Our analytical framework establishes a useful basis with which to examine current and proposed state food regulations, particularly when food manufacturers can make different decisions about how to comply. Below, we consider how food manufacturers responded to three prominent policy examples: (i) Vermont's GM labeling law, (ii) Illinois' sesame labeling law, and (iii) California's food additive law. We use the framework as a lens through which to describe the different margins along which recent state-level regulations impacted food manufacturers.

Policy 1: Vermont's GM Labeling Law

In 2014, Vermont passed a statewide mandatory GM labeling law, which went into effect in July 2016. To comply with the law, food manufacturers could respond to the labeling requirement either by reformulating (i.e., switching to the use of non-GM ingredients) or relabeling (i.e., adding labels indicating the presence of GM ingredients) their products. Research estimating the costs of compliance to federal regulation via relabeling or reformulating has found that, while reformulation is substantially more expensive than relabeling, both tend to be costly endeavors for firms (Muth et al., 2015a; Muth et al., 2015b). For example, reformulation of a low-complexity food (e.g., shelf-stable) is estimated to range from an average of about $50,000 for a minor nonfunctional ingredient to about $650,000 for substitution of a major ingredient (Muth et al., 2015a). However, costs vary across food products and firm types and increase when process time is short (Muth et al., 2015a). Following the enactment of the law, both responses were pursued by different firms; for example, Campbell's Soup Company chose to *relabel* their products to comply with the regulation, while General Mills *reformulated* Cheerios cereal to use non-GM ingredients (Strom, 2016). The regulation forced firms to weigh potential costs from compliance (relabeling or reformulation), separation of production, [12] the possibility of litigation/penalties from noncompliance, and the impacts on variable profits.

A few months prior to the deadline for compliance, many large food manufacturers including Mars, General Mills, and Campbell's announced plans to sell a single version of their products compliant with Vermont's regulations nationwide. NPR weighed in on the topic at the time with a telling headline describing "How Little Vermont Got Big Food Companies to Label GMOs" (Charles and Aubrey, 2016). Our framework can help us understand why many of the largest food firms chose to respond to the law with Option 2.

Beyond the costs of compliance discussed above, we can examine expected changes in variable profits in the regulating market ($\Delta\pi_A$ in the conceptual model). At the time of the decision, many food manufacturers were concerned about GM labels resulting in reductions in demand. The expected effect differed across products; for example, consumers of products marketed for children tended to express greater concerns towards GM ingredients. More recently, research has found that manufacturers' concerns were not unfounded: for example, Fan, Stevens, and Thomas (2022) find that demand decreased by about 5.9% on average for GM-labeled products in the state. For reformulated products, there arguably would have been little resulting change in demand, as the substitution from GM to non-GM ingredients typically does not meaningfully affect most important product characteristics (e.g., taste or appearance). However, the reformulation of products would have raised many producers' variable costs, as the cost of non-GM ingredients would have been higher. Prior work has also documented that the switch by food manufacturers from the use of GM beet sugar to non-GM cane sugar in response to Vermont's law led to an increase in the price of cane sugar (Carter and Schaefer, 2018).

[12] For processed products, separation costs include both separation during production (e.g., separate lines, cleaning) and, potentially, separation during distribution (e.g., separate trucks). The costs associated with separation during production are likely to be more costly and thus more central to firms' decisions.

Second, we can specifically consider the costs of separation (f_S). Maintaining separate products would have been quite costly. Costs would have been highest for firms that sold both a GM and non-GM version of their product, mostly due to the high costs of segregation, monitoring, and certification of non-GM ingredients (Alston and Sumner, 2012). To keep GM and non-GM versions of the product separate, firms would have to segregate GM and non-GM ingredients, separate or clean production lines, and maintain separation post-production during transportation and distribution. Firms choosing to operate separate product lines with and without a GM *label* (rather than GM and non-GM ingredients) would have avoided most of the costliest separation activities, including keeping ingredients and production lines separate. Indeed, at least one company (Schwan's) indicated at the time that they planned to relabel their products for the Vermont market only (D'Ambrosio, 2016). However, even the act of maintaining separation of a product with two different labels during transportation and distribution would still add significant costs. One news story following the law noted, "If you have to manage one product with two labels, that's incredibly complicated. … It's a logistics nightmare." (Spencer, 2016). At least one firm (Danon) attempted to avoid the post-production separation costs completely by asking Vermont grocery retailers to add GMO label stickers to their products upon arrival at stores; however, retailers were not supportive of the plan (D'Ambrosio, 2016).

Third, we can consider the expected costs of violations (θf_L). Vermont's law assigned liability for violations to food manufacturers, and penalties included $1,000 daily fines per product found to be in violation. Both Vermont's attorney general and private citizens were granted the ability to bring civil action for violations, increasing the likelihood and costs of litigation. National attention arguably increased the likelihood of enforcement, and at the time, Vermont's government made clear that it would pursue "willful violators" (Rathke, 2016). Together, these factors signaled that ignoring the law would be costly.

Fourth, we can consider the costs of losing sales to the state (the foregone variable profits $\pi_{\tilde{x},A}$). Given Vermont's small size, in the short term it seems that the optimal decision of some food manufacturers was to simply avoid sales to the state. For example, the Coca-Cola Company indicated at the time that "some lower-volume brands and packages we offer within our broad portfolio could be temporarily unavailable in Vermont" (D'Ambrosio, 2016). However, and in the longer term, food manufacturers at the time seemed to understand and anticipate that similar laws were likely to soon be enacted in other (larger) states. Food manufacturers who chose to exit the Vermont market at the time seem to have done so with the understanding that ending sales in the state was a temporary decision.

While different firms engaged in different responses, the combination of factors elaborated above in conjunction with the results of our conceptual framework helps us understand that Option 1 was prohibitively costly due to high costs of separation (with the correspondingly large value of f_S causing Π^1 to be smaller, all else equal), and Option 4 would be undesirable for most manufacturers given the high likelihood of litigation and penalties (with the correspondingly large value of θf_L causing Π^4 to be smaller, all else equal). As Vermont is a small market, Option 3 would have been a reasonable choice for some firms, especially in the short term, as the opportunity cost of foregone sales ($\pi_{\tilde{x},A}$) would be smaller than the costs of compliance (f_R and

f_S) for many firms. For producers with strong sales in Vermont or who expected additional states to follow suit in establishing similar regulations, Option 2—selling a single version of their product compliant with Vermont's law nationwide—was a commonly observed response. A news story at the time called this choice "the reasonable thing to do" (Spencer, 2016).

Ultimately, following strong lobbying efforts by industry groups, the federal government intervened by creating a single, federal standard for GM labels in July 2016, which superseded Vermont's law. The USDA indicated that this was done to "avoid a patchwork of state labeling regulations that could be confusing for consumers and expensive for manufacturers" (Peikes, 2023).

Policy 2: Illinois' Sesame Allergen Labeling Law

In 2019, the state of Illinois enacted a law requiring specific allergen labeling for food products containing sesame. As with Vermont's GM labeling requirements, food manufacturers could comply with the new rules either by reformulating (i.e., removing sesame) or relabeling (i.e., adding labels indicating the presence or possible presence of sesame) their products.

First, we can explore the costs faced by producers in complying with the law. The costs of compliance (in particular, the cost of reformulation, f_R) would have been comparatively low as relabeling almost exclusively affected products' nutrition facts labels and reformulation was typically undertaken only for products containing small quantities of sesame (e.g., sesame seeds on top of a product) (Muth et al., 2015a; Muth et al., 2015b). Second, we can consider the changes to variable profits ($\Delta\pi_A$). On the consumer side, the effects from the addition of sesame allergen labels were conceivably muted, implying a zero or negligible change in firms' sales from complying with the regulation. For consumers without a sesame allergy, the label would have had little impact on demand. For consumers with an allergy (0.23% of the U.S. population; Gupta et al., 2018) the label could potentially have increased demand, though the aggregate impacts of such effects were conceivably minor. Similarly, there are likely to have been only limited effects on demand attributable to the reformulation of products except in instances where the removal of sesame substantially affected important characteristics of the product (e.g., taste). Third, as described above, the costs of separating products with different sets of ingredients or different labels (f_S) can be very costly. The costs required to produce and transport separate sesame and non-sesame versions of products would have thus imposed a significant burden on both manufacturers and distributors. Fourth, the expected costs of litigation and penalties (θf_L) were also low as the law did not set out any penalties for violations, nor did it explicitly outline any avenues for legal recourse in response to alleged violations. Reports from the time highlighted skepticism by food manufacturers toward the legal requirements to comply, saying, "the validity of the Illinois law is open to question" (van Laack, 2019).[13] Finally, removing products from sale in Illinois (foregoing $\pi_{\tilde{x},A}$) would also have been a costly response for producers given its status

[13] Importantly, the Illinois state law was passed in 2019. At that time there were no national requirements to label sesame as a major allergen. Sesame was added as a major allergen to federal regulation in 2021, and the law went into effect in 2023. Whereas the costs of violating Illinois' law seemed to be low, violating the federal requirements for allergen labeling would result in recalls, penalties, and litigation, which would be expected to be very costly.

as the sixth most populous state, and as with Vermont's GM labeling law, many stakeholders anticipated that the state-level law had the potential to bring on additional regulation across the United States. For example, a news report at the time noted that the Illinois law and manufacturers' responses to it "could easily turn the tide to ensure sesame is disclosed on most items consumers buy throughout the U.S." (Poinski, 2020).

The cost framework would suggest that as costs of separation strongly outweighed the costs of reformulation (f_S was large, causing Π^1 to be smaller, all else equal), most firms would not have been inclined to create distinct versions of their products (Option 1). Similarly, given Illinois' large market size, removing products from the state (Option 3) would have been an undesirable response for most producers (foregone profits $\pi_{\tilde{x},A}$ would be large, reducing the chance that Π^3 would be larger than profits under the other options). In contrast with Vermont's GM-labeling law, the potential costs of violating the state law were low given the limited mechanisms for enforcement and an unclear legal standing. Together, it seems plausible that the optimal response of most food manufacturers would have been to either create a single compliant version to be sold nationwide (Option 2) or sell a noncompliant version nationwide (Option 4).

As with Vermont's law, Illinois' state law helped spur the establishment of national regulation. In 2021, a federal standard for sesame allergen labeling was enacted (the Food Allergy Safety, Treatment, Education, and Research [FASTER] Act), and in 2023 the federal law took effect nationally, formally superseding Illinois' labeling requirements.

Policy 3: California's Food Additive Law

As described above, in 2023, California lawmakers passed bill AB-418, which by 2027 will ban the use of four food additives. In contrast with the two previous examples, the only way for producers to comply with the law is through reformulation, either by removing any of the banned ingredients from their products or substituting any banned ingredients with a legal alternative. Firms cannot comply by relabeling.

First, we can consider the cost of compliance (f_R). As reformulation is the only response by which to comply with the rule, the costs of compliance are more substantial: substituting even a minor ingredient in a product can cost manufacturers between tens of thousands to hundreds of thousands of dollars per product (Muth et al., 2015a). News at the time highlighted the issue, with one headline describing that "California's food additive ban will require the urgent reformulation of 12,000 products" (Hyslop, 2023).

Second, we can consider changes to producers' variable profits ($\Delta\pi_A$). Variable profits would be affected by the differences in input prices and any changes in consumer demand resulting from modifications to the products. For example, synthetic colors like Red Dye No. 3 are generally substantially cheaper than non-synthetic alternatives (FMI, 2024); consequently, reformulating products to remove Red Dye No. 3 would have increased input costs for most firms using it as an ingredient. On the demand side, the probable direction remains ambiguous and depends on product types. For example, consumer demand may *decrease* if the removal of one of the banned additives detracts from attributes such as visual appeal, mouthfeel, shelf life, or other prominent characteristics. However, some consumers also prefer to avoid food additives, a factor which creates the potential for giving rise to *increases* in demand. One news article reported on this issue saying, "Many companies over the years have sought to shed additives to appease consumers' desire for simpler ingredients. But U.S. shoppers have sometimes revolted when food makers switched to more natural, but less colorful and less tasty, alternatives" (Newman, 2024). Products that currently use the regulated food additives include baked goods, candies, frostings, cereals, flours, and beverages (e.g., sodas, juice, sports drinks).

Third, we can consider the cost of separation (f_S). Separation costs in this example were conceivably lower than in the previous two cases, as segregating ingredients would be less expensive, concerns over accidental commingling would be diminished, and recordkeeping requirements would be less onerous. Despite these effects, separation costs are likely to be relatively high, as discussed above, given that keeping two versions of the same product separate during production and distribution can be difficult. One news report weighed in on this issue, saying that creating versions for California and other states would be "complex" for food manufacturers (Hyslop, 2024).

Fourth, we can consider the costs of halting sales of affected products to California (foregone profits $\pi_{\tilde{x},A}$). As California is the most populous state in the country, it would be exceedingly costly for most companies to stop sales to the state.

Finally, we can consider the costs of litigation and penalties (θf_L). The law establishes civil penalties of up to \$5,000 for first violations and up to \$10,000 for subsequent violations, and importantly, allows for a variety of enforcement actions to be taken by legal officials at both the state and local levels. In most cases, the costs to producers of flouting California's regulation would be too expensive to ignore.

Together, the costs associated with firms' potential responses to California's ingredient ban suggest that either ending sales in the state (Option 3) or selling noncompliant versions in California in violation of the regulation (Option 4) are unlikely to be systematically pursued as responses by impacted firms (Π^3 and Π^4) are smaller than profits under the other options due to the typically large magnitudes of f_S and θf_L. Consequently, it is probable that most food manufacturers will reformulate their products in response to the law, and either sell the modified products only in regulating states (Option 1) or in all states (Option 2). For food manufacturers finding that reformulation would have little effect on their profitability, the optimal reaction of firms would arguably be Option 2 in most instances. This would be the most desirable course of action for firms in cases for which reformulation has limited impact on consumers' demand and/or the substitute ingredient is similar in cost to the original. In contrast, for food manufacturers finding that reformulation would have a major impact on profit, pursuing Option 1 would arguably be the optimal decision for most firms.

In the meantime, and as producers weigh their responses to the impending legislation, food manufacturers and industry groups will likely continue to lobby and litigate, hoping for federal preemption and the establishment of nationwide standards that unify the various regulations applied by different states. In the months following the state regulation, the FDA has already followed suit in restricting first BVO and then Red Dye No. 3 at the national level.

Policy Comparisons

Table 1 summarizes the respective types of costs faced by food manufacturers and their expected magnitudes for each of the three policy examples. Together, the three cases show that food manufacturers weigh the respective costs and benefits under each course of action in choosing how to respond to new regulations. For example, Vermont’s small size meant that Option 3—foregoing the relatively small volume of sales to Vermont’s market to avoid a more costly systematic response—was potentially the most viable option for some firms following the state’s GMO labeling requirements. In the case of Illinois’ sesame labeling requirements, the law’s limited scope for litigation and negligible potential for violators of the law to incur penalties meant Option 4 would present the most attractive option for some firms in this particular case. In the case of California’s food additive ban, the potential for changes in product demand following reformulation to comply with California’s law meant that Option 1 would reflect the most profitable choice for firms anticipating a large change in consumer demand from reformulating their products. It is thus important to highlight that, across different settings, firms could profitably pursue any of these options depending on the specific context. However, across the three widely differing policy cases, Option 2, under which manufacturers uniformly adapt their products to the new regulation nationwide, seems to have been a common response pursued by food manufacturers. One key implication of this is that, when faced with substantially different regulatory environments across states, many food manufacturers are likely to respond by conforming to the most restrictive set of state guidelines. A news report discussing the expected responses to the California additive law highlighted this issue, saying, firms’ most straightforward course of action will be “to reformulate for the ‘most strict’ regulations” (Hyslop, 2024). This kind of systematic response from producers in reaction to an ever-evolving policy landscape is likely to have considerable ramifications for the U.S. food industry given the large costs that adjusting to these changes can entail.

While the domestic policy setting reflects fundamental differences with its counterpart(s) in the global arena, the U.S. interstate regulatory environment would arguably be well served in establishing firmer disciplines on such distortions. On the other hand, with regulatory ossification at the federal level, state-level regulation is likely to be an important and potentially powerful option for advocacy groups to effect changes in food policy.

Table 1. Summary of Affected Producer Margins in Case Studies

Cost Type	Case 1: Vermont GM Labeling	Case 2: Illinois Sesame Allergen Labeling	Case 3: California Food Additives
Compliance (reformulation or relabeling)	Can comply either by relabeling (low f_R) or reformulating (high f_R; \$50,000 for a minor non-functional ingredient to about \$650,000 for substitution of a major ingredient; Muth et al., 2015a).	Can comply either by relabeling (low f_R) or reformulating (high f_R).	Only able to comply with reformulation (high f_R).
Change in variable profits (change in demand or change in variable costs)	Relabeling – • Reduced demand ($\Delta q < 0$; demand decreased by about 5.9%; Fan et al., 2022). • Little/no change variable costs ($\Delta c \approx 0$). Reformulation – • Little/no change demand ($\Delta q \approx 0$). • Increased variable costs ($\Delta c > 0$).	Relabeling – • Little/no change demand ($\Delta q \approx 0$; only 0.23% of the U.S. population possesses a sesame allergy). • Little/no change variable costs ($\Delta c \approx 0$). Reformulation – • Little/no change demand ($\Delta q \approx 0$). • Little/no change in variable costs ($\Delta c \approx 0$).	Reformulation – Likely reduced demand ($\Delta q < 0$). Increased variable costs ($\Delta c > 0$).
Separation	Very high cost of separation during production and transportation (f_S). Cost would be higher under reformulation than relabeling.	Very high cost of separation during production and transport (f_S). Cost would be higher under reformulation than relabeling.	High cost of separation during production and transportation (f_S).
Sales to state	Vermont (2nd least populous state) represents a very small portion of demand, thus q is small. However, manufacturers anticipated that other larger states would likely follow suit with similar regulations.	Illinois (6th most populous state) represents a somewhat substantial portion of demand, thus q is medium.	California (most populous state) represents a very large portion of demand, thus q is large. Other states considering additive bans (e.g., New York, Illinois) are also large in size.
Litigation/ penalties	• Law includes penalties (\$1,000/day) and options for litigation ($f_L > 0$). • Positive probability of enforcement ($\theta > 0$).	• Law includes no penalties or options for litigation ($f_L \approx 0$). • Low probability of enforcement ($\theta \approx 0$).	• Law includes penalties (\$5,000/first violation and \$10,000 for subsequent violations) and substantial options for litigation ($f_L > 0$). • Positive probability of enforcement ($\theta > 0$).
Broader conclusions	High separation costs and high costs of potential legal penalties imply that Options 1 and 4 are prohibitively costly in most instances; Options 2 and 3 (uniform reformulation or market exit) present the most attractive options for most firms.	High separation costs and large size of Illinois' market imply that Options 1 and 3 are prohibitively costly in most instances; Options 2 and 4 (uniform reformulation or flouting the regulation) present the most attractive options for most firms.	Large size of California's market and high costs of potential legal penalties imply that Options 3 and 4 are prohibitively costly in most instances; high separation costs reduce the viability of Option 1. Option 2 arguably the most desirable option for most firms.

Note: Authors' construction based on analysis of different components of firms' profits under the three regulatory cases

Future Research

When a new state regulation is passed, food manufacturers must make choices about how to react. Here, we focus on how the costs associated with a regulation determine food manufacturers' optimal production response. In reality, there are likely to be other critical factors and potential reactions that enter into food manufacturers' decision-making process. For example, the possibility of other states creating similar laws or the likelihood of a future federal mandate is likely to influence firms' decision making. Several producers weighed such considerations in the case of Vermont's GM labeling law, in that many food manufacturers correctly anticipated that federal standards would follow in the wake of Vermont's rules. Similarly, beyond making changes in their production and sales decisions, firms and industry groups can (and do) engage in lobbying for their preferred policy outcomes (as has been extensively analyzed in the international trade policy context; see, e.g., Grossman and Helpman, 1995). In our conceptual analysis we assume that the state policy is already in place, in which case lobbying efforts at the state level are conceivably of diminished relevance. However, firms may still engage in lobbying to seek a federal response or to dissuade lawmakers in other states from following suit. Additionally, firms' choices are also likely to vary in relation to producers' attributes, such as the firms' sizes or the types of products that they sell (e.g., branded versus private label products). Further research is needed to understand how food manufacturers' characteristics are related to their decision making under state regulation.

Conclusion

The U.S. regulatory landscape plays host to an increasingly patchwork system of state-level approaches to food policy. As more states pursue individualistic approaches to regulating the food system, food manufacturers must react to this heterogeneity by choosing among several costly responses in adhering (or not) to the new rules and regulations. And, while the recent regulations that we discuss have been implemented under the goal of safeguarding the well-being of consumers, the costs borne from adapting to these new policies—particularly when the specifics of the regulations frequently differ across states—implies that these policy actions do not deliver unmitigated benefits. Finally, though we focus on food manufacturers' decision making in our discussion and analysis, changes in state regulation can clearly have impacts on other stakeholders, most notably consumers.

In this paper we provide a comprehensive overview of this critical and timely issue facing the agri-food system. To help characterize the economic factors that influence firms' responses to changes in states' regulations, we develop a conceptual framework to formally characterize the various considerations weighed by firms in response to these changes, and then apply this framework to analyze three examples of states' food policies. Regardless of which responses individual producers pursue in response to changes in regulation, the increasingly heterogeneous U.S. food policy environment promises to have a sizeable impact on food manufacturers and other actors in the supply chain.

Acknowledgements

We gratefully acknowledge comments on the paper from Bryan Endres and Jonathan Coppess, who provided valuable background on the legal context facing U.S. food and agriculture. We also express our gratitude to the industry representatives who offered important insights into the ways in which food manufacturers have and will continue to respond to the current U.S. food policy environment.

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Appendix

Additional Conceptual Model Details

Equilibrium prices and quantities prior to the regulation and the subsequent response of the firm are given respectively by

$$p_{x,j} = \frac{a_{x,j} + c_x}{2} \quad \text{and} \quad q_{x,j} = \frac{a_{x,j} - c_x}{2b_j} \quad \text{for} \quad j = A, B.$$

From the setup of the model, the firm's prospective profits following the implementation of state A's regulation are given as follows:

Option 1 *(reformulate and separate production)*

$$\Pi^1 = \pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S$$

Option 2 *(reformulate for both markets)*

$$\Pi^2 = \pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R$$

Option 3 *(exit the regulating market)*

$$\Pi^3 = \pi_{x,B}$$

Option 4 *(ignore the regulation)*

$$\Pi^4 = \pi_{x,A} + \pi_{x,B} - \theta f_L$$

The firm will optimally choose the option that maximizes its expected profits in response to the regulation. Define $\Delta\pi_A = \pi_{\tilde{x},A} - \pi_{x,A}$ and $\Delta\pi_B = \pi_{\tilde{x},B} - \pi_{x,B}$ as the differences in the firms' variable profits in states A and B, respectively, from selling the reformulated version of the product in the each market.

Firm optimally chooses Option 1 ($\Pi^1 > \Pi^2, \Pi^3, \Pi^4$)

- For $\Pi^1 > \Pi^2$,

$$\pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S > \pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R$$

$$\pi_{x,B} - f_S > \pi_{\tilde{x},B}$$

$$-f_S > \Delta\pi_{x,B}$$

- For $\Pi^1 > \Pi^3$,

$$\pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S > \pi_{x,B}$$

$$\pi_{\tilde{x},A} - f_R - f_S > 0$$

- For $\Pi^1 > \Pi^4$,

$$\pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S > \pi_{x,A} + \pi_{x,B} - \theta f_L$$

$$\pi_{\tilde{x},A} - f_R - f_S > \pi_{x,A} - \theta f_L$$

$$\Delta\pi_A - f_R - f_S > -\theta f_L$$

Firm optimally chooses Option 2 ($\Pi^2 > \Pi^1, \Pi^3, \Pi^4$)

- For $\Pi^2 > \Pi^1$,

$$\pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R > \pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S$$

$$\pi_{\tilde{x},B} > \pi_{x,B} - f_S$$

$$\pi_{\tilde{x},B} - \pi_{x,B} > -f_S$$

$$\Delta\pi_B > -f_S$$

- For $\Pi^2 > \Pi^3$,

$$\pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R > \pi_{x,B}$$

$$\pi_{\tilde{x},A} + \pi_{\tilde{x},B} - \pi_{x,B} - f_R > 0$$

$$\pi_{\tilde{x},A} + \Delta\pi_B - f_R > 0$$

- For $\Pi^2 > \Pi^4$,

$$\pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R > \pi_{x,A} + \pi_{x,B} - \theta f_L$$

$$\pi_{\tilde{x},A} - \pi_{x,A} + \pi_{\tilde{x},B} - \pi_{x,B} - f_R > -\theta f_L$$

$$\Delta\pi_A + \Delta\pi_B - f_R > -\theta f_L$$

***Firm optimally chooses Option 3* ($\Pi^3 > \Pi^1, \Pi^2, \Pi^4$)**

- For $\Pi^3 > \Pi^1$,

$$\pi_{x,B} > \pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S$$

$$0 > \pi_{\tilde{x},A} - f_R - f_S$$

- For $\Pi^3 > \Pi^2$,

$$\pi_{x,B} > \pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R$$

$$0 > \pi_{\tilde{x},A} + \Delta\pi_B - f_R$$

- For $\Pi^3 > \Pi^4$,

$$\pi_{x,B} > \pi_{x,A} + \pi_{x,B} - \theta f_L$$

$$0 > \pi_{x,A} - \theta f_L$$

Firm optimally chooses Option 4 $(\mathbf{\Pi^4} > \mathbf{\Pi^1}, \mathbf{\Pi^2}, \mathbf{\Pi^3})$

- For $\Pi^4 > \Pi^1$,

$$\pi_{x,A} + \pi_{x,B} - \theta f_L > \pi_{\tilde{x},A} + \pi_{x,B} - f_R - f_S$$

$$\pi_{x,A} - \theta f_L > \pi_{\tilde{x},A} - f_R - f_S$$

$$-\theta f_L > \pi_{\tilde{x},A} - \pi_{x,A} - f_R - f_S$$

$$-\theta f_L > \Delta\pi_A - f_R - f_S$$

- For $\Pi^4 > \Pi^2$,

$$\pi_{x,A} + \pi_{x,B} - \theta f_L > \pi_{\tilde{x},A} + \pi_{\tilde{x},B} - f_R$$

$$-\theta f_L > \pi_{\tilde{x},A} - \pi_{x,A} + \pi_{\tilde{x},B} - \pi_{x,B} - f_R$$

$$-\theta f_L > \Delta\pi_A + \Delta\pi_B - f_R$$

- For $\Pi^4 > \Pi^3$,

$$\pi_{x,A} + \pi_{x,B} - \theta f_L > \pi_{x,B}$$

$$\pi_{x,A} - \theta f_L > 0$$

Journal of Food Distribution Research
Volume 56, Issue 1, pp. 27–42

An Assessment of Profitability Using Monte Carlo Simulation Approach: A Case of Georgia Blueberry Industry

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Abstract

Our study assesses the profitability of producing blueberries using a drip irrigation system by addressing the price and yield variability. We use deterministic and stochastic budgeting approaches. We extend the deterministic budget to the stochastic budget using Monte Carlo simulation and applying triangular distributions to blueberry prices and yield in Georgia. The net present value (NPV) of returns from a blueberry investment under a deterministic budget is 1 to 3 times greater than under a stochastic budget. Under the stochastic approach, we study returns from blueberries by classifying growers based on their performance; thus, the study has direct implications particularly for Georgian and southeast growers in making investment decisions. Furthermore, the results will be helpful to farmers, researchers, and farm risk analyzers in assessing agricultural investment.

Keywords: blueberry, budget, Monte Carlo simulation, price, stochastic

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Introduction

The stochastic nature of key parameters, such as policy, production, and economic variables inherently complicates agricultural decision making. This complexity is accentuated in the agricultural sector due to its unique and diverse risks, including institutional (policy and regulations), production (disease and weather), and economic (input and output prices) risks (Harwood et al., 1999; Thorne and Hennessy, 2007). These risks introduce volatility in pricing and production outcomes, necessitating a comprehensive approach to uncertainty management in agricultural business decisions.

Variability in prices and yields represents significant risks in agriculture, impacting the predictability of farm income (Goodwin and Ker, 2002). Traditional methods that rely on historical averages may not capture the full spectrum of potential outcomes, making them insufficient in today's variable markets (Carter and Dean, 1960; Grant, 1985). Consequently, adopting a probabilistic approach to account for uncertainties in yield and price provides a more reliable basis for decision making, accommodating the unpredictable nature of factors like market demand fluctuations and climatic conditions.

This study enhances the traditional enterprise budgeting tool, a critical decision-making resource developed by extension teams at land-grant universities for various agricultural commodities and practices. Traditionally, these budgets have utilized a deterministic approach, tailored to specific growing conditions and inputs but have failed to account for the inherent variability in key factors, such as output quantity and price. By introducing stochastic elements into the budgeting process, this research adapts enterprise budgets to reflect better the uncertainties faced by blueberry growers in Georgia, providing a more robust framework for financial planning and risk assessment in agriculture.

Blueberry is one of Georgia's top 10 fruits and nuts commodities in terms of farm gate value, with a share of 42.3%, and contributed 2.45% of the total Georgia agricultural farm gate value in 2022 (University of Georgia, 2024). According to the 2022 Georgia Farm Gate Value Report (2024), the total farm-gate value of blueberries was $449.4 million from 27,192 acres, produced from 118 out of 159 counties in the state. Bacon County has been the top producer in the state, with the highest farm gate value in the past eight years.

Deterministic and Stochastic Budget

A deterministic budget provides financial outcomes based on fixed parameter values and assumes stable economic conditions, often not reflective of real-world scenarios (Fonsah and Hudgins, 2007; Fonsah et al., 2010; Fonsah et al., 2018). In contrast, a stochastic budget incorporates uncertainty and randomness, evaluating potential outcomes across a spectrum of variables rather than relying on fixed inputs. This method is particularly effective in non-stationary environments where variability is inevitable. The stochastic model utilizes variable estimates to predict likely outcomes, thus integrating risk and uncertainty into financial projections (Elkjaer, 2000; Richardson, 2006). Employing the Monte Carlo simulation technique, stochastic budget extends beyond single-point estimates to offer a probabilistic view that reveals the distribution of potential outcomes, providing deeper insights into the dynamics of agricultural economics.

Georgia blueberry growers suffer price and output changes due to the cultivar used in production, production area, aggregate productivity, market, and timing (Fonsah and Hudgins, 2007; Fonsah et al., 2007; Fonsah et al., 2011). However, despite pricing and output variations, Georgia blueberry growers usually rely on deterministic enterprise budgets, which are usually the type of enterprise budgeting decision tools made available by extension specialists at land-grant universities. Awondo, Fonsah, and Gray (2017) found that the grower's profit is overestimated by at least three times in a deterministic budget. Thus, we aim to incorporate risk associated with random variables like price and yield into Georgia's blueberry budget and present a probabilistic approach to evaluating returns on blueberry investment in Georgia. Our specific objectives are to (i) revisit the deterministic blueberry budget for Georgia, (ii) transform the deterministic budget to a stochastic budget, and (iii) compare net present values (NPV) from the two budget systems.

Several studies have used a probabilistic approach in farm enterprises. For example, Gummow and Patrick (2000), Rayburn (2009), Shalloo et al. (2004), and Werth et al. (1991) have utilized probabilistic approaches in the animal sector, whereas Elkjaer (2000), Ludena et al. (2010), Clancy et al. (2012), and Awondo, Fonsah, and Gray (2017) used them in the plant sector. Elkjaer (2000) recognizes Stochastic Budget Simulation (SBS) as a tool to estimate the overall cost to avoid statistical dependencies between variables. Ludena et al. (2010) present a greenhouse stochastic budgeting model incorporating risk to compare the production costs of flowers, taking pricing and flowering into account as stochastic components. Clancy et al. (2012) use nontraditional budgeting to estimate returns from willow and miscanthus in Ireland. Similarly, Awondo, Fonsah, and Gray (2017) consider price and yield as associated risk variables and provide the probability distribution of net present value and break-even year from producing muscadine grapes in Georgia.

For the past five years (2018–2023), the University of Georgia College of Agricultural and Environmental Sciences Extension (UGA-CAES) prepared deterministic budgets for southern highbush blueberry. Fonsah et al. (2007) and Kunwar and Fonsah (2022) introduced the risk-rated budget analysis approach for southern highbush blueberries, whereas Fonsah (2008, 2011) developed one for rabbiteye blueberries. These papers use sensitivity analysis to evaluate the effect of price and yield fluctuations that capture the risk component that could affect trends in blueberry production. The what-if analysis allows us to evaluate net returns in a few different price-yield scenarios; however, it does not allow us to project the whole range of net returns (in between and out of the designated case). Building upon the deterministic budgets in Kunwar and Fonsah (2022), we develop a stochastic budget for blueberry growers in Georgia to set a new, more realistic standard for enterprise budgeting in blueberry production.

Methodology

Deterministic Budget

To develop a deterministic budget, we considered two components, costs and returns, based on an acre of producing Southern Highbush blueberries in Georgia for a fresh market. We developed the budgets for a production system using a drip irrigation system and plant density of about 1,210 per acre and a planted distance of 12 feet apart in a row and 3 feet between rows.

A newly planted orchard will be fully productive in its fourth year. However, approximately 25% of blueberries can be harvestable from the second year of establishment (Fonsah et al., 2007; Kunwar and Fonsah, 2022). For the analysis of costs and returns in different years of production, we used the first three years as orchard establishment and the fourth and subsequent years as the full productive years. We collected input prices from farmers and agricultural vendors during the 2020 Annual Blueberry Growers Meeting. The input price information is private and confidential, making accessing comprehensive data from farmers challenging. Therefore, we consulted with extension county agents who maintain close relationships with the farming community. We calculated average prices for our analysis to address the variability in input prices, which may arise due to factors, such as the purchase volume, the vendor's relationship with the grower, or the payment terms (cash versus credit).

Total production costs were determined by estimating fixed and variable costs. Variable costs encompass land preparation, planting, fertilizers, weed and pest control, interest on operating capital, and harvesting and marketing expenses. Fixed costs include expenditures on tractors and equipment, overhead, management, and irrigation systems. Harvesting and marketing costs cover harvesting, custom packing, cooling, handling, and brokerage fees, which may vary annually depending on yield fluctuations. However, we assumed these costs would remain constant once the orchard reaches the full productive years, as we adopted a fixed yield for those years.

To estimate costs associated with machinery and other equipment, we used standardized practices recommended by the Agricultural and Applied Economics Association (AAEA) Task Force on Commodity Costs and Returns (AAEA, 2000). We assumed machinery and equipment costs as of the price of 2020. We estimated the costs of machinery and equipment based on 10 acres because their full efficiency is not obtained if used under 4 acres (Fonsah et al., 2007; Bogati et al., 2023; Magar, Fujino, and Han, 2024). However, we later adjusted these costs by an acre to harmonize with other costs. We included parameters, such as percentage used for the crop, purchase price, salvage value, lifespan, depreciation, interest, tax, and insurance in all machinery and equipment costs. The calculation used a salvage value of 20%, an interest rate of 6.5%, and 1.5% as taxes and insurance (Kunwar and Fonsah, 2022). We assumed farmers would use all the new equipment when establishing a blueberry farm.

For the returns side of the blueberry production, we estimated the price per pound (lb.) and the yield per acre based on multiple meetings and focus group discussions with growers, county agents, and blueberry economists. We used 15 years of production to estimate costs and returns, although blueberries can be harvested from an orchard for more than 15 years by adopting good agricultural practices (GAP). We used the blueberry price of $3 per lb., assuming it would remain constant throughout production. The expected yields for the second and third years are 1,700 lbs. and 4,000 lbs./ acre, respectively, whereas from the fourth year onward, it is 7,000 lbs./acre. Accounting for a 5% loss during harvesting and packaging, adjusted yields in years 2, 3, and 4–15 are 1,615 lbs., 3,800 lbs., and 6,650 lbs./acre, respectively.

To appraise the investment in blueberry production in Georgia, we calculated the net present value (NPV) of cash flows for 15 years. NPVs were estimated at two discount rates of 2% and 5% to capture the variability in the personal discount rate of growers.

Stochastic Budget

Unlike the deterministic budget, we described blueberry yield and price as random components and defined their distributions. We allowed simulation to model blueberry price and yield in Georgia. The costs were derived from input prices while acknowledging the challenge of capturing the variability of all input prices (Shrestha, 2015). Thus, we did not incorporate variability in input prices and used single-point estimates from the deterministic budget. Finally, we calculated NPVs from the total costs and the simulated yields and prices and used a probabilistic approach to evaluate NPVs. We applied the Monte Carlo simulation using triangular distribution for both price and yield.

Monte Carlo Simulation Using Triangular Distribution

Defining the probability distribution to model the price and yield in crop production is noteworthy during risk assessment and management (Ramirez, McDonald, and Carpio, 2010). We fitted the triangular distribution to represent the yield and the price variability of blueberries in Georgia.[1] The triangular distribution is used when we have small sample data (Hardaker et al., 2015) and to model agricultural price and yield data because the time series price and yield data for long periods are rare (Ramirez, McDonald, and Carpio, 2010). Moreover, the triangular distribution can define yield and price distribution when experts identify the minimum, maximum, and most likely values (Back, Boles, and Fry, 2000). We used the inversion of the cumulative distribution function (CDF) of triangular distribution for the simulation, which we discuss below.

Probability density function ($f(x)$) and cumulative distribution function ($F(x)$) of a triangular distribution with the parameters a (minimum), b (maximum), and c (most likely) are given by,

$$f(x) = \frac{2(x-a)}{(b-a)(c-a)}, \qquad if\ x \in [a,c] \tag{1}$$

$$= \frac{2(b-x)}{(b-a)(b-c)}, \qquad if\ x \in [c,b] \tag{2}$$

$$F(x) = \frac{(x-a)^2}{(b-a)(c-a)}, \qquad if\ x \in [a,c], \qquad say\ P_1 \tag{3}$$

$$= 1 - \frac{(b-x)^2}{(b-a)(b-c)}, \qquad if\ x \in [c,b], \qquad \text{say } P_2 \tag{4}$$

[1] We assume independence between prices and yields to simplify the analysis, making it accessible for extension agents and growers. This assumption aligns with the practical scope of data collected from a select group of participants at an annual meeting, where individual production levels are unlikely to influence market prices significantly.

In Figure 1, $x_1 = c - a$, $x_2 = b - c$, and the area of ΔT_1 gives the probability of x less than or equal to c.

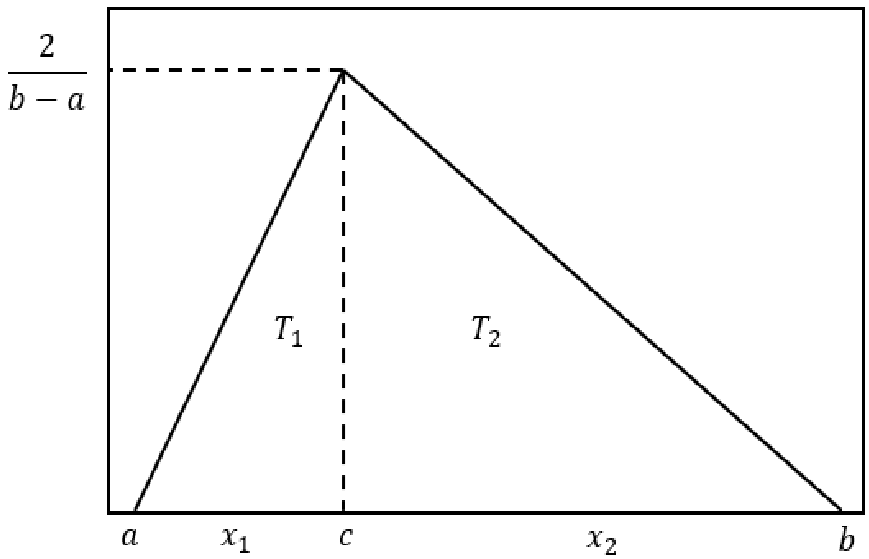


Figure 1. The Probability Distribution Function (PDF) of the Triangular Distribution

Mathematically,

$$P(x \leq c) = area\ of\ \Delta T_1 = \frac{1}{2} \times (c-a) \times \frac{2}{(b-a)} = \frac{c-a}{b-a} \tag{5}$$

Now, taking equation (5) as a reference, if any random probability is smaller than *P (x ≤ c)*, we use the inverse function of equation (3) to get x_1 and, if any random probability is greater than *P (x ≤ c)*, we use the inverse function of equation (4) to get x_2.

$$P_1 = \frac{(x-a)^2}{(b-a)(c-a)} \qquad if\ x \in [a, c] \tag{6}$$
$$or, x = a + \sqrt{P_1 \times (b-a) \times (c-a)}$$

$$P_2 = 1 - \frac{(b-x)^2}{(b-a)(b-c)} \qquad if\ x \in [c, b] \tag{7}$$
$$or, x = b - \sqrt{(1-P_2) \times (b-a) \times (b-c)}$$

P(x) is a random probability between 0 and 1. So, for *P(x) ≤ P (x ≤ c),* we use $P_1 = P(x)$ and $x_1 = x$ from equation (6) and for *P(x) >P (x ≤ c)*, we use $P_2 = P(x)$ and $x_2 = x$ from equation (7).

Simulation Step

For the simulation process in this study, the price and the yield were the input variables, and the NPV was the output variable. We allowed for the simulation of the yield from years 4 to 15 and the price from years 1 to 15. We obtained NPVs following the steps mentioned below.

i. For each year from 4 to 15, we defined triangular distribution for yield by using maximum, minimum, and most likely yield to generate random yields in Equations (6) and (7).
ii. We applied step (a) for the price for each year from 1 to 15.
iii. To calculate the revenue for the corresponding years, we randomly selected yield and price in different years.
iv. From the net cash flows derived using the revenue generated above in (c), we computed NPVs at 2% and 5% discount rates.
v. We iterated the process from (a) to (d) 10,000 times.

Survey Design

A questionnaire was distributed to blueberry growers via email and personal meetings at the Annual Blueberry Growers Meeting in Alma County, Georgia, on January 8, 2020. A total of 40 responses were obtained; 5 responses were received through email, and 35 were gathered from personal interviews at the grower's meeting. The questionnaire asked respondents to provide historical annual yield and price data for up to 15 years if the farmers were able to keep historical records. If not, it asked the farmers to provide the expected maximum, minimum, and most likely price and yield if they were to grow blueberries for the next 10 years, given their experience growing blueberries in Georgia.

Results and Discussions

Deterministic Budget

The total cost of plants per acre (with a density of 1,210/acre) was $2,783 due to the $2.30 cost each for healthy and ready-to-plant blueberry bushes. Labor cost/acre was $242, and the total land preparation cost was $2,773/acre. In the first year of the establishment, the total operating costs were $6,947/acre.[2] The total operating costs in the second and third years of the establishment were $1,458 and $1,437 per acre, respectively. The total harvesting and marketing costs in the second and third years were $3,375 and $7,942 per acre, respectively. In full production years, the total operating cost was estimated at $1,646/acre, and the harvesting and marketing costs were estimated at $13,899/acre.

[2] For a comprehensive breakdown of these costs across different years, see Kunwar and Fonsah (2022). This reference provides an extensive categorization of costs and is a complementary resource to our analysis.

In the first three establishment years, the total variable costs were estimated at $6,947.26/acre, $4,833.65/acre, and $9,379/acre, respectively. The total variable costs were estimated at $15,544.24/acre for each full productive year. The observed decrease in the total variable costs in the second year from the year can be attributed to a lack of costs for land preparation, planting, and planting materials. Also, there is an increase in the total variable costs from the second to the third year. The yield in the third year increased compared to the second year, making the harvesting and marketing/packaging costs higher in the third year. Similarly, the total fixed costs estimated for years 1, 2, 3, and 4–15 were $2,849.46/acre, $2,026.11/acre, 2,022.92/acre, and $2,054.23/acre, respectively, which included a fixed machinery cost of $1,521.3/acre every year.

Table 1 shows the cash flows for the 15 years of production and the calculated NPVs at 2% and 5% discount rates. The investment in blueberry production begins to yield positive returns from the third year and covers the original cost of the investment in the ninth year. The net present value at both discount rates was positive, implying that NPVs at discount rates between 2% and 5% are positive. Thus, the returns from blueberry production are profitable, making the investment attractive for Georgia growers.

Table 1. Cash Flows and NPVs of Blueberry Production in Georgia, 2020

Year	Yield	Price	Return	Variable Cost	Returns over Variable Cost	Total Cost	Returns over Total Cost (Net Cash Flow)
1	0	3	0	6,947.26	-6,947.26	9,796.72	-9,796.72
2	1,615	3	4,845	4,833.65	11.35	6,859.77	-2,014.77
3	3,800	3	11,400	9,379.00	2,021.00	11,401.92	-1.92
4–15	6,650	3	19,950	15,544.24	4,405.76	17,598.47	2,351.53

NPV at a discount rate of 2% (NPV@2%) = 12,128.70
NPV at a discount rate of 5% (NPV@5%) = 7,187.17

Note: Yield is measured in lbs. per acre, and returns, costs, and price are measured in dollars per lb. Values for years 4 to 15 are the same; thus, we do not report to save space.

Stochastic Budget

Table 2 shows the average maximum, minimum, and most likely yields and prices obtained from the blueberry growers. Since the variation in maximum and minimum prices and yields were high, we classified blueberry producers into different categories based on prices and yields obtained.

Table 2. Summary Statistics of Expected Maximum, Minimum, and Most Likely Yield and Price of Blueberry Growers in Georgia, 2020

	Mean	Standard Deviation	Minimum	Maximum
Minimum yield	3,456.76	1,980.40	900.00	8,000.00
Most likely yield	6,459.46	2,514.90	2,000.00	12,000.00
Maximum yield	10,910.81	4,415.87	4,000.00	20,000.00

Minimum price	1.42	0.98	0.20	4.00
Most likely price	2.39	1.25	0.65	5.00
Maximum price	4.04	1.92	1.00	7.50

Note: Yield in lbs. per acre and price in dollars per lb. Source: Survey and authors' calculations.

Based on yield, we classified growers as "Top Producers" if their yield is above the average most likely yield and "Low Producers" if their yield is below the average most likely. Similarly, based on price, growers were categorized as "High-Price Receivers" if the received price was above the average most likely and "Low-Price Receivers" if the received price was below the average most likely. We calculated the average of maximum, minimum, and most likely yield and price for all categories. Interacting categories based on the price and yield, we have four groups of growers—"top producers receiving high prices (TPRHP)," "low producers receiving high prices (LPRHP)," "top producers receiving low prices (TPRLP)," and "low producers receiving low prices (LPRLP)," (see Table 3).[3] We also include the group "growers in general" without categorization. Figure 2 shows the CDFs for all the groups after simulation.

Table 3. Categorization of Georgia Blueberry Growers Based on the Price Received and the Yield, 2020

Panel A:

			Yield					
			Top Producer			**Low Producer**		
		Price	**a 4,833.33**	**c 8,638.89**	**b 13,777.78**	**a 2,152.63**	**c 4,394.74**	**b 8,194.74**
High price receiver	a	2.14						
	c	3.57		TPRHP (27.27%)			LPRHP (18.18%)	
	b	6.00						
Low price receiver	a	0.48						
	c	1.52		TPRLP (24.24%)			LPRLP (30.30%)	
	b	2.60						

Panel B:

	TPRHP	**LPRHP**	**TPRLP**	**LPRLP**
Yield range	8944.45	6042.11	8944.45	6042.11
Price range	3.86	3.86	2.12	2.12

Note: a, b, and c denote average minimum, average maximum, and average most likely, respectively. TPRHP represents top producers receiving high prices, LPRHP represents low producers receiving high prices, TPRLP represents top producers receiving low prices, and LPRLP represents low producers receiving low prices. Figures in the parentheses are the percentage of growers belonging to the group based on the most likely price and the most likely yield.

Higher prices for greater yields give more returns, so there was a 100% chance of obtaining positive NPV at 2% and 5%. Therefore, for the TPRHP, blueberry production in Georgia is highly

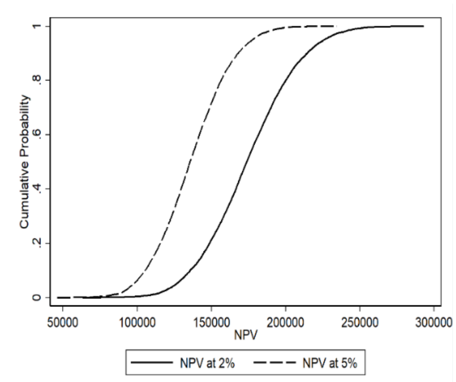
[3] Our study categorizes growers based on yield and price but does not explicitly link these categories to their risk preferences. Understanding the risk aversion of different groups could enhance the analysis, and we recommend this as an avenue for future research.

profitable. Figure 2a presents the cumulative distribution function of NPV respectively at two different discount rates. Unlike the TPRHP, blueberry production for the TPRLP is not conducive to investment. The chance of getting a positive NPV during the 15 years of production is almost 0% at 2% and 5% discount rates (see Figure 2b).

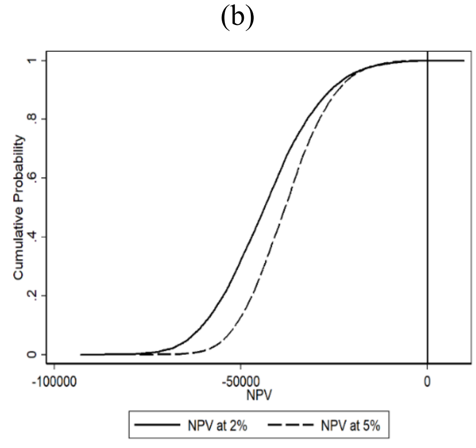
The chance of a positive NPV decreases from 100% to 67.72% and 63.63% at the discount rate of 2% and 5%, respectively, if a producer belongs to LPRHP fails to maintain the productivity of the farm (see Figure 2c). Because the probability is greater than 50%, the investment in the production of blueberries is favorable.[4] Growers in the category LPRLP do not obtain positive NPV during the 15 years of blueberry production. This category of farmers has a 0% chance of paying back the cost of their original investment (see Figure 2d).

The probability of getting a positive NPV for the "growers in general" at a 2% discount rate is 30.24%, and at 5%, it is 23.85% (see Figure 2e). These probabilities incorporate all the possible combinations of yields and prices. As the chance of a positive NPV is below 50%, the investment in blueberry production does not seem favorable in Georgia.

(a)



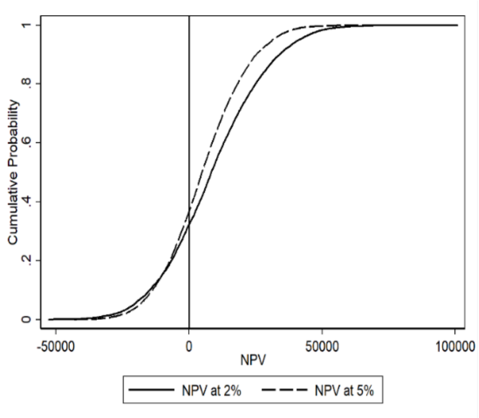
(b)

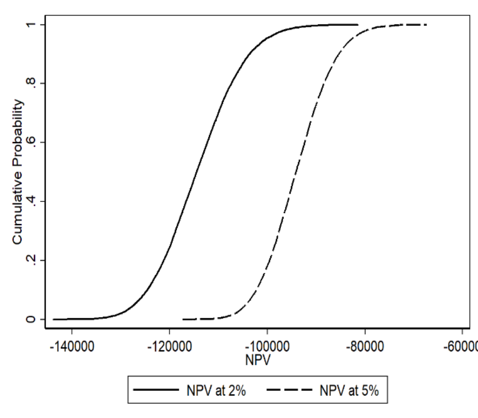


(c)

(d)

[4] The 50% threshold used in this analysis is a conventional benchmark, where an investment is considered favorable if the likelihood of achieving a positive NPV exceeds the likelihood of a loss. These standards balance risk and potential return and are suited to the moderate risk tolerance typical in agricultural investments. We leave it to future studies to explore alternative probability thresholds for evaluating investment favorability under conditions of uncertainty.





(e)

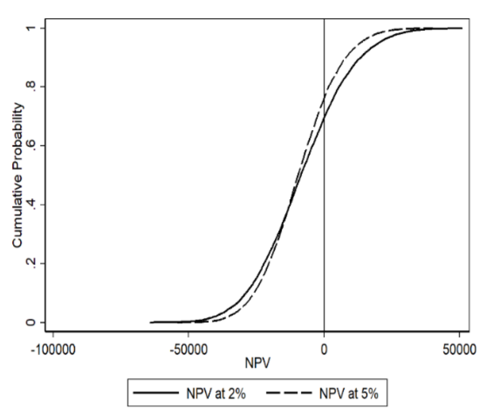


Figure 2: Cumulative distribution functions of net present values for blueberry producers in Georgia, 2020 (a) top producers receiving high prices (b) top producers receiving low prices (c) low producers receiving high prices (d) low producers receiving low prices (e) growers in general

Comparison and Discussion of Results from Deterministic Budget vs. Stochastic Budget.

Table 4 presents the expected NPV from the deterministic budget and stochastic budget for all categories of producers. The comparison shows that the expected NPV from the traditional budget is only possible if a grower falls in the "top producer receiving high price group." The expected NPVs from the deterministic budgets do not fall in any producers' 95% confidence interval, including the "growers in general." This discrepancy underscores a key distinction between the two budgeting approaches.

Table 4. Comparison of NPV from the Deterministic and Stochastic Budget in Georgia, 2020

	Discount Rate	Expected NPV	Lower Bound (95% CI)	Upper Bound (95% CI)	Chance of Positive NPV (%)
Deterministic budget	2%	12,129			100
	5%	7,187			100

Stochastic budget					
TPRHP	2%	174,579	173,987	175,172	100
	5%	136,449	135,975	136,924	100
TPRLP	2%	-43,387	-43,648	-43,127	0
	5%	-37,851	-38,059	-37,642	0
LPRHP	2%	9,122	8,754	9,491	67.72
	5%	5,567	5,270	5,864	63.63
LPRLP	2%	-114,231	-114,391	-114,070	0
	5%	-93,868	-93,997	-93,739	0
Growers in general	2%	-8,157	-8,480	-7,834	30.24
	5%	-9,174	-9,433	-8,915	23.85

Note: NPV in dollars per acre. TPRHP represents top producers receiving high prices, LPRHP represents low producers receiving high prices, TPRLP represents top producers receiving low prices, and LPRLP represents low producers receiving low prices.

There is a 100% chance of a positive NPV for the TPRHP and a 0% chance for the LPRLP. The results show no chance of a positive NPV for the TPRLP. However, there is a significant chance of a positive NPV for the LPRHP. Analyzing the difference between the maximum and minimum yields and prices within the TPRLP and the LPRHP categories can provide valuable insights into why LPRHP might exhibit a higher potential for positive NPV but not the TPRLP.

Table 3 shows that while the TPRLP has a yield range that is 1.48 times wider than the LPRHP (8,944.45 vs. 6,042.11 lbs. per acre), the LPRHP's price range is 1.82 times wider than that of the TPRLP ($3.86 vs. $2.12 per lb.). The TPRLP experiences high yield variability, which could buffer against low prices. However, the lower and narrow price range limits their potential profitability. Lower prices diminish the benefits of high yields because the returns per unit are reduced. The LPRHP has lower yield variability, suggesting consistent and predictable production. The higher and wider range of prices compensates for its lower yields. This signals that high prices ensure substantial net revenue even with modest yields. Thus, growers need to focus on determinants of blueberry prices such as the berries' quality, harvesting time, strategic marketing windows, and bargaining power (Kader, 2002; Yeh et al., 2023).

To contrast traditional and nontraditional budgets, comparing the expected NPV from the conventional budget to the expected NPV from the stochastic budget for the "growers in general" group makes more sense because both are estimated for all the blueberry producers in Georgia. The expected NPV in the deterministic budget is 248.70% more than the expected NPV in the stochastic budget at a 2% discount rate and 178.34% at a 5% discount rate. The considerable difference in expected NPVs from different budget systems shows that the result from the traditional budget is unrealistic and unjustifiably optimistic. Our results align with those of Awondo et al. (2017), who depicted that the chance of getting a positive NPV from the non-stochastic budget is 3 to 4 times greater than that from the stochastic budget. The chance of a positive NPV for the "top producers receiving high prices" (100%) is close to the findings of Fonsah et al. (2007), establishing a 92% estimated chance for profit in southern highbush blueberry production in Georgia. Similarly, the estimated chances of a positive NPV for the "low producers receiving high prices" (67.72% and 63.63% at the discount rate of 2% and 5%) are close to the figures obtained by Kunwar and Fonsah (2022), whereby an estimated 69% chance for profit was prescribed for southern highbush blueberry production using drip irrigation and frost protection in Georgia.

Conclusion

The paper discusses blueberry's profitability using two different kinds of budgets—deterministic and stochastic. For the simulation of prices and yields to develop a stochastic budget, we defined the triangular distribution using the minimum, maximum, and most likely values because the stochastic variable is better delineated by distribution. Thus, we interpreted the stochastic budget results using the chance (%) of getting a positive NPV at two discount rates, 2% and 5 %. Unlike the stochastic budget, the non-stochastic budget has a straightforward interpretation.

The expected NPV in the deterministic budget is $12,129/acre at a 2% discount rate and $7,187/acre at a 5% discount rate. Except for a group of producers with high production and who receive high prices, no other groups have NPV higher than in the deterministic budget with 100%. The NPVs at 2% and 5% for a group "top producer receiving high price" are expectedly high, constituting 27.27% of blueberry growers in Georgia. Also, no chance of positive NPVs for a group of producers with low production and receiving low prices was estimated. We found no chance of positive NPVs in a group of "top producers receiving low prices."

In contrast, a significant percentage of positive NPVs in a group "low producers receiving high prices" was observed, signaling price as a critical determining factor for higher returns on investment. Specifically, a more relevant comparison between NPVs for the group "growers in general" and NPVs from the deterministic budget shows that a deterministic budget projects notably higher (1 to 3 times) NPVs than the stochastic budget. Despite negative expected NPVs for a group of "growers in general," there is a certain chance (23.85%–30.24%) of getting a positive NPV.

This study was primarily focused on farmer-level prices and yield of blueberries, for which data from the primary source are critical. Any data from the secondary source could be used as a reference but is irrelevant to making farmer-level conclusions. Because the price and yield data of the commodity are confidential and growers are concerned about it, we found it difficult to obtain primary data for such kinds of studies.

A limitation of this study is that we do not consider costs (input prices) as stochastic variables. Considering input prices as random variables and applying a similar approach improves the study's findings and is a possible extension of our work. Finally, the takeaway message is that depending solely on the deterministic enterprise budget can mislead farmers regarding investment and returns. The estimates from the traditional assessment approach can underestimate or overestimate the real production scenarios of any farm crop. A better understanding of all the potential stochastic variables and proper definition of their distributions yields more accurate and precise estimates of the outcome variables.

While stochastic budgeting helps model uncertainty in agricultural economics, its adoption across the farm industry is restricted by computational complexity and a widespread lack of specialized training. Recognizing these barriers, it is crucial for Extension Agricultural Economists at land-grant universities to elevate their educational offerings, emphasizing training in stochastic budgeting techniques. Developing a stochastic budget that complements the traditional partial enterprise budgets produced annually for various horticultural crops can improve decision making among growers.

Our study is based on data from specific grower categories in Georgia, which may not fully reflect the broader variability in agricultural practices or market dynamics. As such, the findings are primarily applicable within similar environmental and economic contexts. Future research should explore these dynamics across more diverse regions to enhance the generalizability of our results.

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Journal of Food Distribution Research
Volume 56, Issue 1, pp. 43–65

Changes in U.S. Shopper Attitudes about Shopping Lists, Private Labels, and Self-Checkouts

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Abstract

The Covid-19 pandemic changed many consumer behaviors. This research replicates three studies that used a 2015 survey to learn whether shopping list use, private-label perceptions, or self-checkout preferences shifted. A July 2022 survey (N = 1,399) of U.S. adults found that shopping list use appeared to have decreased, and demographics continued to provide little help in profiling users. Direct perceptions of private-label riskiness increased, some relationships changed, and there was a greater willingness to serve meals made with private labels to guests. Shoppers who were older or who experienced higher technology anxiety continued to dislike self-checkouts.

Keywords: consumer behavior; demographics; privacy concerns; impulsivity; technology anxiety; risk preferences; time preferences

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Introduction

The COVID-19 pandemic and related policies were linked to many consumer behavior changes during 2020 and 2021. Literature reviews noted "profound and transformative" impacts for retailers and suggested that there would be long-term consequences (Verhoef, Noordhoff, and Sloot, 2023; Yao et al., 2024). Some customers felt "forced" to shop for groceries online (Tyrvainen and Karjaluoto, 2022), and others did not want to interact with store employees (Shamim, Ahmad, and Alam, 2021). Ghost kitchens (i.e., prepare food without seating) grew in the United States during the pandemic, and online ordering and delivery were projected to remain strong (Chen and House, 2022; Li and Fisher, 2022). In the United States, people became accustomed to doing things in their homes instead of going out, and the frequency of outdoor activities in 2022 was below the level in 2019 (Shi and Goulias, 2024). Surveys in several countries suggested that consumers wanted to continue many of their new behaviors (e.g., Charm et al., 2020 [US]; Gupta and Mukherjee, 2022 [India]; Galushko and Riabchyk, 2024 [Canada]; Kumar and Pole, forthcoming [US]). Other research found strong interest in returning to pre-pandemic shopping and consumption behaviors (e.g., Sorrentino, Leone, and Caporuscio, 2022 [Italy]; Lee et al., 2022 [US]; Inoue and Todo, 2023 [Japan]; Handrinos et al., 2023 [US]). Following the pandemic, grocery visits quickly returned to near normal levels in Germany and the United States (Bruggemann and Olbrich, 2023; Dennis-Bauer, Jaller, and Amador, 2024); Walmart laid off more than 2,000 workers who fulfilled website orders (Valinsky, 2023); and many U.S. ghost kitchens were closed (Creswell, 2024). Questions about the pandemic's long-term effects on consumer shopping behaviors remain unanswered.

This paper focuses on three consumer traits—shopping list use, private label preferences, and interest in using self-checkouts—and examines whether relationships shifted between 2015 and 2022, pre- versus post-pandemic. This research considers questions such as, "Did shopping list use change?", "Did the profiles shift for people who believe private label purchases are risky?", and "Did attitudes toward self-checkouts improve or deteriorate?" The objective is to replicate three prior studies (Larson, 2018, 2019a, 2022) using the same survey methodology to determine whether the identified associations changed between 2015 and 2022. After the updated findings for the three traits have been examined, this study's implications and limitations are summarized.

Literature Review

Shopping Lists

Shopping lists can help consumers plan purchases, check to see if important needs are met when shopping, and save both time and money (Larson, 2022). A summary of 14 industry-funded studies suggested that age, gender, marital status, and ethnicity can help profile frequent shopping list users (Larson, 2022, Table 1). However, these studies did not use multivariate analysis or test for statistical significance. Another set of 26 academic studies was reviewed, and several suggested that age, gender, and household size may be related to list use (Larson, 2022, Table 2). However, much of the cited research was more than 20 years old and no new research has been found since the 2022 paper. Larson (2022) compared the regression results from six surveys and concluded that demographics could not consistently identify list users. The two significant factors were privacy concerns and impulsivity.

One survey reported that people were more likely during the pandemic to make a list before shopping (Breen, 2020). A possible contributing factor was the economic challenges faced by households that may have encouraged more planning to limit nonessential purchases. Consumers shopped more online (Dennis-Bauer, Jaller, and Amador 2024), and they used a list while buying online, which tends to reduce spending (Davydenko and Peetz 2020). During the early part of the pandemic, store traffic at supermarkets in Northern Ireland decreased and transaction sizes increased (Boyle et al., 2022). Thus, lists might make less frequent store trips more efficient. If list use increased during the pandemic for online or offline shopping, we might expect some people to continue making lists. This leads to two hypotheses:

> H1: Shopping list use during 2022 was higher than in 2015.
>
> H2: Privacy concerns and impulsivity will continue to identify list users while demographics will not identify them.

Private Labels

Because demographic segmentation cannot identify likely private-label buyers, targeting specific demographic groups with promotions is not efficient (Larson, 2018). To identify possible segments to target, Larson (2018) profiled the shoppers who believed that buying private labels was risky and who would not serve products with private labels to guests in their homes. The perception that private labels were risky was linked to education, risk preferences, and impulsivity. Attitudes about serving private-label products to guests were associated with gender, education, income, risk and time preferences, and impulsivity measures. These variables could be used for targeting information about private-label quality.

When households experience economic challenges, private-label sales often increase. Between 2019 and 2023, private-label dollar sales in the United States increased by 34.2% (Circana, 2024). In addition to the economic downturn, supply chain problems during the pandemic meant some shoppers did not find their favorite brands. The economic pressure and brand switching (i.e., private-label trial) could have reduced the perceived riskiness of private labels (Pinto et al., 2022). Stores also increased the availability of private labels. The resulting trial and distribution gains may have enhanced private-label reputations and encouraged repeat purchases. U.S. private-label shares also rose when the pandemic ended (Mookherjee et al., 2024). These factors may have increased shopper comfort levels when buying private labels and serving them to guests, leading to four hypotheses:

> H3: Perceptions of private-label riskiness during 2022 were lower than in 2015.
>
> H4: Perceptions of private-label riskiness will continue to be associated with education, risk preferences, and impulsivity measures.

> H5: Willingness to serve private labels to guests during 2022 was higher than in 2015.
>
> H6: Willingness to serve private labels to guests will continue to be associated with gender, education, income, risk and time preferences, and impulsivity measures.

Self-Checkouts

Larson (2019a) reported that two variables were associated with lower interest in self-checkouts, older age groups and technological anxiety. Several other surveys noted the importance of age (e.g., Fernandes and Pedroso, 2017; Lee and Lyu, 2019). For example, 56% of Americans preferred staffed checkouts when given a choice between them and self-checkouts (Shriber, 2023). However, only 40% of those aged 25 to 44 preferred staffed checkouts compared to 66% of those aged 55 and older who preferred staffed checkouts. Technology anxiety could also limit the use of self-service technology (e.g., Demoulin and Djelassi, 2016; Lee and Lyu, 2019; Lian, 2021; Duarte et al., 2022). A review of 22 studies from the hospitality and tourism fields confirmed this relationship (Shiwen, Kwon, and Ahn, 2022).

Several other measures have been linked with self-service technology interest, including privacy concerns (e.g., Safaeimanesh et al., 2021; Sohn, Schnittka, and Seegebarth, 2024). Reliability and risk of failure tended to affect interest in using the technology (Fernandes and Pedroso, 2017; Baabdullah et al., 2019; Le, Hill, and Troshani, 2022; Thomas-Francois and Somogyi, 2023; Ingale et al., 2024). Therefore, risk preferences may be important. Customers may perceive self-service systems to be faster and choose them to save time (Amorim et al., 2016; Rinta-Kahila et al., 2021; Xu, Jeong, and Baiomy, 2022). Also, time preferences may affect checkout choices (Park, Kim, and Hyun, 2021). Some studies suggest that social influence or obligation could increase technology use (e.g., Bulmer, Elms, and Moore, 2018; Baabdullah et al., 2019; Hamza, Maidawa, and Muhammed, 2019; Jeon, Sung, and Kim, 2020; Liang, Lee, and Workman, 2022). Therefore, social desirability bias (SDB) may affect self-checkout preference scores. These other measures were not significant in 2015 but may be important in 2022.

Many changes have occurred since 2015. Stores have added self-checkouts and shoppers tried self-checkouts during the pandemic (to reduce contact with store employees). Recent data suggest that nearly 40% of U.S. grocery cash registers are self-checkouts (CapitalOne Shopping, 2024). Approximately 30% of supermarket transactions involved self-checkouts in 2023, nearly double the percentage in 2018 (Baker, 2024). The wider availability and trial during the pandemic may have boosted acceptance, leading to the final two hypotheses:

> H7: Preference for using self-checkouts during 2022 was higher than in 2015.
>
> H8: Age and technology anxiety will continue to identify those who preferred using self-checkouts and privacy concerns and risk and time preferences. Social desirability bias measures are also significant.

Methodology

The earlier studies used a survey, fielded in October 2015 by Qualtrics, a professional marketing research company. It randomly selected adults aged 25 to 65 from online panels. The original sample had 605 subjects. Subsequent analysis identified one outlier, a respondent whose demographic responses were unreasonable. Therefore, the October 2015 analyses shown in this paper were run with 604 respondents. The 2015 sample profile, shown in Table 1, was similar to the U.S. population, except that nonwhites were underrepresented.

To replicate the October 2015 results, Qualtrics fielded another survey in July 2022. After data cleaning (e.g., removing straight-line responses), Qualtrics provided 1,405 responses. Six respondents were dropped for being far outside the target age range, leaving a sample size of 1,399. Qualtrics reported that at least 250 responses came from each of the four U.S. Census regions, indicating good geographic diversity. The respondent demographic profile, shown in Table 1, was similar to the U.S. population, except that females were overrepresented.

Shopping Lists

The dependent variable was based on the statement, "I usually prepare a shopping list before I go grocery shopping." Between 2015 and 2022, the percentage who agreed or strongly agreed with the statement (using a 7-point Likert scale) fell from 62.7% to 56.6%. The average response score was also significantly lower in 2022 than in 2015 (see Table 1), in contrast to H1.

Table 1. Profiles of Survey Respondents

Demographic Measures and Other Variables	Proportion of the Oct. 2015 Sample	Proportion of the July 2022 Sample
Female	0.68	0.72
Nonwhite	0.14	0.45
Age 35 to 44 years	0.21	0.29
Age 45 to 54 years	0.25	0.21
Age 55 years or higher	0.36	0.28
Single/widowed/divorced (i.e., not married)	0.39	0.50
Some college (including 2-year degree)	0.42	0.44
College graduate (4-year degree or more)	0.33	0.26
Presence of children in the household	0.36	0.41
Household income of $40,000 to $79,999	0.34	0.31
Household income of $80,000 to $119,999	0.16	0.10
Household income of $120,000 or more	0.07	0.08
Household size of 2 members	0.34	0.30

Table 1 (cont.)

Demographic Measures and Other Variables	**Proportion of the Oct. 2015 Sample**	**Proportion of the July 2022 Sample**
Household size of 3–4 members	0.36	0.37
Household size of 5 members of more	0.12	0.14
First born with (younger) brothers or sisters	0.28	0.30
Mixed-handed (i.e., not strong left- or right-handed)	0.48	0.47
Social desirability bias score average (range 0 to 16)	6.79	7.25
Risk tolerance score (insurance deductibles) average (range 2 to 14)	8.56	8.25
Risk concern score (compared to others) average (range 2 to 14)	9.07	9.16
I usually prepare a shopping list before I go grocery shopping (average)	5.61	5.35
The decision to try a store brand (private label) food product involves risk	3.61	3.79
If I were preparing a meal for guests, I would only buy brand-name ingredients (average)	3.73	3.40
When buying a few items at a grocery store, I prefer using self-checkouts (where I scan the groceries myself) (average)	4.38	5.14
Sample size	604	1,399

Larson (2022) used factor analyses to construct environmental attitudes, privacy concerns, and impulsivity variables. The green attitudes factor was formed from responses to a six-item scale (Haws, Winterich, and Naylor, 2014) that reflects environmental attitudes. To measure privacy concerns, principal component analysis was employed using scale items from Smith, Milberg, and Burke (1996) and Parasuraman and Igbaria (1990). After varimax rotation, the results in Table 2 were similar to those from the prior survey, except that one item ("Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information") moved from the first factor to the third factor. Impulsivity was assessed with the Hausman (2000) scale. Table 3 shows the results from both surveys after varimax rotation. Although the factor structures were the same, one item ("I go shopping to watch other people") fit the structure better in 2015. Other research could explore whether this result reflects a shift in shopping attitudes.

Table 2. Privacy Scale Varimax-Rotated Factor Scores for 2022 Survey

	Information Protection Factor	Technology Anxiety Factor	Data Errors/ Authorization Factor
It bothers me to give personal information to so many companies	**0.764**	0.317	0.018
When companies ask me for personal information, I sometimes think twice before providing it	**0.754**	0.156	0.142
People should refuse to give information to a business if they think it is too personal	**0.684**	-0.033	0.192
Companies should take more steps to make sure that the personal information in their files is accurate	**0.596**	-0.084	0.492
Computer databases that contain personal information should be protected from unauthorized access—no matter how much it costs	**0.539**	-0.053	0.473
Companies should never sell the personal information in their computer databases to other companies	**0.490**	-0.034	0.410
I am easily frustrated by computerized bills	-0.046	**0.715**	-0.121
I am anxious and concerned about the pace of automation in the world	0.094	**0.704**	-0.008
I am sometimes frustrated by increasing automation in my home	-0.084	**0.689**	-0.004
Sometimes I am afraid that data processing department will lose my data	0.043	**0.558**	0.283
Computers are a real threat to privacy in this country	0.306	**0.520**	0.017
Company should take more steps to make sure that unauthorized people cannot access personal information in their computers	0.062	0.086	**0.802**
Companies should have better procedures to correct errors in personal information	0.282	0.084	**0.744**
Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information	0.500	-0.100	**0.539**
Cronbach's alpha		0.771	

Note: Bold indicates the largest score for an item.

Table 3. Factor Scores for Impulsive Behavior Scale after Varimax Rotation

	October 2015		July 2022	
Items from the Hausman (2000) Impulsive Behavior Scale	**Hedonic Buying Factor**	**Impulsive Trait Factor**	**Hedonic Buying Factor**	**Impulsive Trait Factor**
Shopping satisfies my sense of curiosity	**0.871**	0.185	**0.801**	0.164
I feel like I'm exploring new worlds when I shop	**0.858**	0.168	**0.773**	0.132
I like to shop for the novelty of it	**0.842**	0.261	**0.735**	0.287
Shopping offers new experiences	**0.814**	0.071	**0.747**	0.115
I go shopping to be entertained	**0.803**	0.288	**0.745**	0.248
I get a real high from shopping	**0.806**	0.296	**0.727**	0.269
I go shopping to watch other people	**0.363**	0.289	**0.296**	0.249
I often buy things without thinking	0.190	**0.835**	0.132	**0.837**
"Buy now, think about it later" describes me	0.173	**0.800**	0.234	**0.701**
Sometimes I'm a bit reckless about what I buy	0.098	**0.802**	0.069	**0.773**
I often buy things spontaneously	0.264	**0.784**	0.255	**0.759**
"Just do it" describes the way I buy things	0.223	**0.707**	0.323	**0.686**
Sometimes I feel like buying things on the spur of the moment	0.175	**0.680**	0.190	**0.656**
If I see something I want, I buy it	0.248	**0.640**	0.362	**0.441**
Cronbach's alpha	0.913		0.891	

Note: Bold indicates the largest score for an item

A social desirability bias (SDB) indicator was included in the models. SDB occurs when some respondents change their answers for impression management, self-deception, or identity definition (Larson, 2019b). SDB can affect results when a significant portion of the sample tends to change their answers to match social expectations, and these individuals all perceive the same social norm that guides them to adjust in the same way. In this study, the 16-item scale by Stober (2001) was used to identify subjects who tend to adjust their answers to be consistent with social norms. The raw score for each individual ranged from 0 to 16, and a logistic transformation was used, as suggested by Larson (2019b).

Private Labels

The October 2015 and July 2022 surveys included a direct question and an indirect question to assess perceived private-label risks: "The decision to try a store brand (private label) food product involves risk," and "If I were preparing a meal for guests, I would only buy brand-name ingredients." The average scores for the questions, shown in Table 1, were significantly different, with more agreeing that buying private labels was risky in July 2022 (not supporting H3) and less agreeing that subjects would only buy brand-name ingredients to prepare a meal for guests (supporting H5). One possible explanation for these conflicting trends is that the reaction of guests may not be the only type of risk that concerns prospective private-label buyers. This possibility could be explored in other research. Responses of at least "somewhat agree" (top-three-box) served as the dependent variables in binary logistic regressions.

Because this analysis deals with perceived purchase risks, respondent risk preferences may be important. Instead of trying to directly assess risk preferences (which is difficult), four proxy variables were used to test the importance of risk preferences. The first measure, risk tolerance (insurance deductibles), sums the scores from two questions: "If I were shopping for homeowners or renters insurance, I would prefer a policy with a higher deductible and lower costs over a policy with higher rates and better coverage," and "If I were shopping for car insurance, I would choose a policy with a higher deductible and lower costs over a policy with higher rates and better coverage." The second measure, risk concern (compared with others), combines two questions: "I tend to be more concerned about harmful risks than my friends and neighbors," and "I tend to avoid taking risks more than my neighbors and friends." Another risk proxy variable is birth order. Later-borns tend to take more risks than first-borns (Krause et al., 2014). Studies of company founders in China and business managers in Kosovo found that first-borns were more risk-averse (Zheng et al., 2021; Lajci, Berisha, and Krasniqi, 2022). The final risk measure was handedness. Mixed-handed subjects tended to focus on an activity's perceived risks while consistent-handed people focused on the perceived benefits (Christman et al., 2007).

Like risk preferences, time preferences are difficult to directly assess. The surveys included four questions, answered with 7-point Likert scales, that dealt with today-focus: "The joy in my life comes from what I am doing now, not from what I will be doing later," "I try to live one day at a time," "I tend to focus on what is going on now instead of what will happen in the future," and "If I take care of the present, the future will take care of itself." A factor analysis combined them into one variable.

Self-Checkouts

The dependent variable is based on responses to the following statement: "When buying a few items at a grocery store, I prefer using self-checkouts (where I scan the groceries myself)."

The average score increased, consistent with H7. All of the independent measures in the model have been defined previously. Ordered probit regressions identify which variables contributed to higher (or lower) scores for self-checkout preferences.

Results

Shopping Lists

The results from the ordered probit regressions are shown in Table 4. For the July 2022 regression, the female variable was significant and positive. Women and married subjects gave shopping lists higher scores in the July 2022 survey, but not in the October 2015 survey. The green attitude factor was also significant in July 2022, but not in October 2015. Three measures were significant in both surveys. Two privacy concern factors, information protection and data errors/authorization, were both positive, which implies that list users had above-average privacy concerns. The impulsive trait factor was negative in both surveys; list users tend to be less impulsive. Two other measures—hedonic shopping and SDB—were significant and positive in July 2022 and not in the prior survey. The hedonic shopping factor suggested that users enjoyed shopping. The positive score also contributes indirectly to greater impulsivity, contrasting with the negative coefficient on the impulsive trait factor. The positive coefficient on SDB implied that some believed using shopping lists was socially expected.

Table 4. Ordered Probit Regressions for Using Shopping Lists

	October 2015			**July 2022**		
	B	**S.E.**	**T-Stat**	**B**	**S.E.**	**T-Stat**
Female	0.3064	0.1677	1.8271	**0.4193***	0.1074	3.9029
Nonwhite	-0.4561	0.2366	-1.9275	-0.1465	0.1012	-1.4471
Age 35–44 years	-0.0622	0.2530	-0.2458	-0.1622	0.1380	-1.1757
Age 45–54 years	0.0259	0.2548	0.1016	-0.1014	0.1511	-0.6710
Age 55 years or more	-0.1563	0.2491	-0.6277	0.1306	0.1502	0.8696
Single, divorced, widowed	-0.3345	0.1761	-1.8993	**-0.2474***	0.1036	-2.3879
Some college (including 2-year degree)	-0.0713	0.1976	-0.3607	0.0931	0.1187	0.7844
Four-year college degree or more	-0.0099	0.2232	-0.0442	0.1036	0.1408	0.7360
Income $40,000–$79,999	0.1295	0.1914	0.6765	-0.0282	0.1126	-0.2507
Income $80,000–$119,999	**0.6108***	0.2663	2.2934	0.0707	0.1751	0.4039
Income $120,000 or more	-0.0385	0.3192	-0.1206	-0.1898	0.1897	-1.0009
Household size 3–4 members	-0.0007	0.1807	-0.0041	-0.0463	0.1133	-0.4086
Household size 5 members or more	-0.0057	0.2712	-0.0211	-0.0887	0.1572	-0.5640
First born with brothers/sisters	**-0.4020***	0.1730	-2.3237	0.0970	0.1063	0.9126
Green attitudes factor	0.0553	0.0870	0.6361	**0.2798***	0.0600	4.6679
Information protection factor	**0.1663***	0.0792	2.0998	**0.1576***	0.0523	3.0147
Technological anxiety factor	0.0974	0.0825	1.1811	0.0646	0.0552	1.1707

Table 4 (cont.)

	October 2015			July 2022		
	B	**S.E.**	**T-Stat**	**B**	**S.E.**	**T-Stat**
Data errors/authorization factor	**0.3603***	0.0848	4.2516	**0.1485***	0.0528	2.8127
Hedonic shopping factor	0.0186	0.0881	0.2117	**0.2166***	0.0581	3.7264
Impulsive trait factor	**-0.4877***	0.0842	-5.7917	**-0.2168***	0.0543	-3.9897
Social desirability bias (transformed)	0.1251	0.2100	0.5956	**0.5332***	0.1336	3.9915
Dallas area	0.0076	0.3012	0.0252	0.2373	0.1586	1.4956
Seattle area	-0.7461	0.3872	-1.9267	0.1821	0.2559	0.7116
Denver area	-0.3874	0.4820	-0.8039	0.3169	0.3148	1.0066
Phoenix area	**0.7654***	0.3313	2.3101	-0.0846	0.2247	-0.3765
Intercept 1|2	-3.5001	0.3993	-8.7648	-2.9844	0.2361	-12.6406
Intercept 2|3	-2.5537	0.3642	-7.0123	-1.9494	0.2118	-9.2030
Intercept 3|4	-2.1949	0.3561	-6.1630	-1.5240	0.2070	-7.3625
Intercept 4|5	-1.7836	0.3502	-5.0923	-0.9871	0.2036	-4.8477
Intercept 5|6	-0.5913	0.3432	-1.7228	0.1091	0.2022	0.5396
Intercept 6|7	0.4603	0.3432	1.3414	1.3528	0.2056	6.5810

Note: * and bold indicate significant at the 5% level

The Larson (2022) paper included a third Qualtrics survey, fielded in January 2015. Regressions with this data also found significant positive coefficients for female, green factor, hedonic shopping factor, and SDB variables. Although these four measures were not significant in the October 2015 data, their significance in July 2022 should lead future researchers to consider them in their studies. Marketers might also use these measures to design messages that resonate with shopping list users. The main conclusions from the Larson (2022) paper were generally confirmed: demographics provide little information for identifying list users, while privacy concerns and impulsivity are significant, supporting H2.

Private Labels

The results from the binary logistic regressions involving the perception that private labels are risky are shown in Table 5. Only part of H4 was supported. While college education was an important measure in October 2015, it was not significant in July 2022. This finding suggests that college education may not be useful for targeting private-label quality information. Older respondents (55 years and over) did not agree that private labels were risky in July 2022. However, that variable was not significant in October 2015. Two proxies for risk preferences suggested that people who were concerned about risk (or more tolerant of risk) also believed private-label products were risky purchases. In the 2022 regression, both impulsivity factors were significant and positive. These results suggest that some tactics suggested by Larson (2018) (e.g., targeting people who enjoy shopping, staging informative sampling events, offering satisfaction guarantees, etc.) could continue to be effective options to convert skeptical consumers into private-label buyers.

Table 5. Binary Logistic Results for Top-Three-Box: Purchasing Private Label Products Is Risky

	October 2015			July 2022		
	B	S.E.	*P*-value	B	S.E.	*P*-value
Female	0.029	0.202	0.884	-0.020	0.136	0.883
Nonwhite	0.259	0.273	0.343	0.174	0.124	0.159
Age 35–44 years	-0.302	0.299	0.313	0.130	0.165	0.432
Age 45–54 years	-0.328	0.294	0.264	0.014	0.184	0.941
Age 55 years or more	-0.170	0.282	0.547	**-0.374***	0.186	0.044
Single, divorced, widowed	-0.081	0.245	0.741	0.114	0.136	0.400
Some college (including 2-year degree)	**0.549***	0.246	0.026	-0.151	0.145	0.299
Four-year college degree or more	**0.636***	0.277	0.021	-0.258	0.179	0.148
Income $40,000–$79,999	0.173	0.230	0.452	0.044	0.142	0.756
Income $80,000–$119,999	0.487	0.299	0.103	0.245	0.215	0.253
Income $120,000 or more	0.321	0.400	0.423	0.443	0.240	0.065
Household size 2 members	0.031	0.328	0.925	-0.221	0.190	0.245
Household size 3–4 members	-0.312	0.324	0.335	-0.221	0.189	0.243
Household size 5 members or more	-0.218	0.417	0.601	-0.394	0.232	0.089
Risk tolerance (insurance deductibles)	0.051	0.033	0.120	**0.090***	0.022	0.000
Risk concern (compared to others)	**0.083***	0.042	0.049	**0.131***	0.026	0.000
First born with brothers/sisters	**-0.563***	0.216	0.009	-0.228	0.134	0.089
Mixed-handedness	-0.249	0.185	0.178	0.127	0.121	0.295
Today-focus factor	0.148	0.099	0.137	0.064	0.066	0.332
Hedonic shopping factor	**0.294***	0.100	0.003	**0.270***	0.069	0.000
Impulsive trait factor	0.061	0.099	0.535	**0.210***	0.063	0.001
Constant	**-1.959***	0.714	0.006	**-2.487***	0.422	0.000

Note: * and bold indicate significant at the 5% level

Table 6 shows the regression for people who said they would only serve food made with name-brand ingredients to guests. In both October 2015 and July 2022, men tended to agree. In October 2015, education and income were important measures, but not in July 2022, so only part of H6 was supported. Education and income may not be useful for segmentation. Single-member households tended to agree with the statement in 2022. Perhaps targeting smaller households might improve private-label sales. The three nondemographic concepts, risk preferences, time preferences, and impulsivity, were significant in 2015 and 2022. These results confirm the importance of using in-store promotions and addressing risk concerns when communicating with customers about private labels.

Table 6. Binary Logistic Results for Top-Three-Box: Buy Brand-Names for Meals Served to Guests

	October 2015			July 2022		
	B	**S.E.**	***P*-value**	**B**	**S.E.**	***P*-value**
Female	**-0.490***	0.204	0.016	**-0.674***	0.150	0.000
Nonwhite	0.169	0.283	0.552	0.123	0.140	0.379
Age 35–44 years	-0.108	0.313	0.731	0.070	0.186	0.707
Age 45–54 years	-0.090	0.306	0.769	0.000	0.211	0.999
Age 55 years or more	0.245	0.292	0.403	0.028	0.207	0.892
Single, divorced, widowed	-0.067	0.252	0.791	-0.035	0.155	0.822
Some college (including 2-year degree)	**0.572***	0.254	0.024	0.021	0.163	0.899
Four-year college degree or more	**0.654***	0.286	0.022	-0.324	0.205	0.114
Income $40,000–$79,999	0.177	0.237	0.455	0.122	0.161	0.449
Income $80,000–$119,999	**0.628***	0.306	0.041	0.100	0.245	0.684
Income $120,000 or more	**0.821***	0.411	0.046	0.508	0.271	0.061
Household size 2 members	0.089	0.341	0.793	**-0.531***	0.215	0.014
Household size 3–4 members	0.023	0.331	0.944	-0.260	0.210	0.215
Household size 5 members or more	-0.760	0.451	0.092	**-0.613***	0.264	0.020
Risk tolerance (insurance deductibles)	-0.012	0.034	0.713	**0.057***	0.025	0.020
Risk concern (compared to others)	**0.100***	0.044	0.023	**0.140***	0.030	0.000
First born with brothers/sisters	**-0.564***	0.221	0.011	**-0.359***	0.155	0.021
Mixed-handedness	-0.222	0.191	0.246	-0.178	0.138	0.197
Today-focus factor	**0.301***	0.105	0.004	**0.299***	0.077	0.000
Hedonic shopping factor	**0.391***	0.104	0.000	**0.587***	0.081	0.000
Impulsive trait factor	0.171	0.102	0.093	**0.255***	0.071	0.000
Constant	**-1.677***	0.739	0.023	**-2.117***	0.466	0.000

Note: * and bold indicate significant at the 5% level

Self-Checkouts

The results of the self-checkout analysis are shown in Table 7. Like in the October 2015 survey, the July 2022 analysis found older respondents and those with higher technology anxiety were less interested in using self-checkouts. Technology anxiety was unrelated to age; the correlation was 0.09. The July 2022 regression had other significant variables, supporting all the measures listed in H8. The two privacy concern factors were both significant and positive, suggesting that retailers who want to promote self-checkout use should take extra steps to protect customer privacy. The today-focus factor was significant, so stores could highlight the potential time savings from using self-checkouts (although professionals can often scan purchases faster, self-checkout users may have biased time perceptions [Djelassi, Diallo, and Zielke, 2018]). Both impulsivity factors were significant and positive. Retailers might want to merchandise impulse-driven items near self-checkout stations.

Two variables were not significant in October 2015, and were positive and significant in July 2022. Married respondents expressed more interest in using self-checkouts. However, households with children did not express more or less interest. The significant SDB measure suggests that some respondents believed that using self-checkouts was socially expected. Studies on self-checkouts that do not control for SDB may overstate interest in the technology.

Table 7. Ordered Probit Regressions for Using Self-Checkouts

	October 2015			**July 2022**		
	B	**S.E.**	**T-Stat**	**B**	**S.E.**	**T-Stat**
Female	-0.094	0.159	-0.593	-0.007	0.107	-0.066
Nonwhite	0.339	0.232	1.460	-0.164	0.100	-1.646
Age 35–44 years	-0.177	0.243	-0.729	-0.083	0.136	-0.613
Age 45–54 years	**-0.602***	0.241	-2.494	**-0.447***	0.150	-2.987
Age 55 years or more	**-0.945***	0.235	-4.018	**-0.925***	0.153	-6.048
Single, divorced, widowed	-0.118	0.168	-0.703	**-0.245***	0.101	-2.433
Some college (including 2-year degree)	-0.045	0.186	-0.242	0.063	0.117	0.536
Four-year college degree or more	-0.201	0.211	-0.951	-0.007	0.140	-0.053
Children present	0.022	0.174	0.126	0.031	0.109	0.282
Income $40,000–$79,999	0.011	0.180	0.060	0.173	0.112	1.542
Income $80,000–$119,999	0.214	0.237	0.906	-0.189	0.173	-1.089
Income $120,000 or more	0.196	0.331	0.592	0.177	0.194	0.913
Green attitudes factor	0.107	0.085	1.259	-0.013	0.059	-0.218
Information protection factor	0.048	0.076	0.633	**0.190***	0.052	3.689
Technological anxiety factor	**-0.201***	0.082	-2.440	**-0.241***	0.056	-4.337
Data errors/authorization factor	0.042	0.079	0.528	**0.202***	0.053	3.836
Risk tolerance (insurance deductibles)	0.050	0.028	1.811	0.022	0.018	1.215
Risk concern (compared to others)	0.030	0.037	0.809	-0.019	0.023	-0.831
Today-focus factor	0.009	0.083	0.111	**0.144***	0.057	2.530

Table 7 (cont.)

Hedonic shopping factor	0.073	0.085	0.857	**0.121***	0.059	2.049
Impulsive trait factor	0.002	0.084	0.020	**0.179***	0.054	3.305
Social desirability bias (transformed)	0.188	0.208	0.906	**0.397***	0.136	2.914
Intercept 1|2	-1.768	0.541	-3.270	-3.203	0.335	-9.576
Intercept 2|3	-0.965	0.536	-1.800	-2.418	0.325	-7.445
Intercept 3|4	-0.449	0.535	-0.840	-1.995	0.322	-6.205
Intercept 4|5	-0.020	0.534	-0.038	-1.279	0.318	-4.022
Intercept 5|6	0.704	0.535	1.317	-0.426	0.316	-1.347
Intercept 6|7	1.586	0.539	2.943	0.819	0.318	2.578

Note: * and bold indicate significant at the 5% level

Implications and Limitations

This study found that shopping list usage, the profiles of people who believed private-label purchases were risky, and the attitudes toward self-checkouts changed between 2015 and 2022. For shopping lists, usage decreased and demographics continue to provide little help in identifying users (with the possible exception of gender). Lower list use suggests that more shoppers may not plan their trips, so store merchandising may generate more impulsive purchases. List users also tended to have higher privacy concerns. These concerns may limit list user excitement about loyalty programs. List users also were concerned about the environment, enjoyed shopping, and believed list use was socially expected. Marketers could use these traits to design messages that appeal to this group. Showing images of shoppers enjoying shopping while using a list, scheduling sampling and other events in stores, and offering incentives for bringing reusable bags could appeal to this group.

The private-label attitude changes were mixed. Although private-label sales in the United States have grown, retailers need to continue marketing the items. Demographics, with the possible exceptions of gender and household size, provide little guidance for market segmentation and targeting. Targeting the consumers who believed the purchases were risky with product information could be successful. Other tactics could include highlighting single-serve, masculine, premium, or indulgent products that are easy to prepare. Images could show consumers having fun while shopping, and informative store displays could introduce private labels to new buyers.

Interest in using self-checkouts appeared to be higher in 2022. However, attitudes were negatively associated with age. The generations model of consumer behavior would suggest that, as older generations die off, acceptance of the technology may increase. However, if the lifestage model applies to self-checkout use, as people age they would adopt the attitudes that are typical of older shoppers and acceptance would not improve (Larson, 2019a). Technology anxiety also tended to limit self-checkout use. Stores could install self-checkout systems that generate less anxiety or add more fun to the experience (Fernandes and Pedroso, 2017; Shin and Dai, 2022; Reid et al., 2024).

One factor making self-checkouts attractive to stores is their potential to reduce labor costs. However, the reasons shoppers assign to their deployment (e.g., improve service or lower costs) can influence their reactions (Nijssen, Schepers, and Belanche, 2016; Van de Sanden, Willems, and Brengman, 2022). Some shoppers may feel empowered by the self-checkouts, while others may be disempowered (Schweitzer and Simon, 2021; Kim and Chen, 2025). Differences in the need for human interaction may also split shoppers into segments (Chen et al., 2018; Kim, Kim, and Lee, 2023). For shoppers who prefer human interaction, the clerks at staffed registers should strive to enhance shopper experiences. Stores should describe self-checkouts as part of their efforts to improve customer service and make users feel empowered.

Some stores periodically close staffed checkouts, so all customers must use self-service during those times. A literature review concluded that customers should not be forced to use self-service (Baer and Leyer, 2018), as forcing may reduce future patronage (Feng et al., 2019). Another problem with self-checkouts is intentional theft. A survey by LendingTree found that 15% of shoppers who used self-checkouts confessed to intentional stealing (Davis, 2023). The self-check-out theft (shrink) rate of 3.5%–4% is about four times the rate for purchases at staffed check-outs, leading some to question their deployment (Basiouny 2024). A benefit of staffed check-outs is they can boost customer loyalty (Sharma, Ueno, and Kingshott, 2021; Nusrat and Huang, 2024). However, when a chain eliminated self-checkouts, some customers were disappointed (Rinta-Kahila et al., 2021). Therefore, stores may want to continue providing some self-checkouts.

Like most studies, this research is not without limitations. Because the data are from surveys, this study measured attitudes instead of actual behaviors. The samples either underrepresented nonwhites or overrepresented women. Measure interactions were not tested, and some important variables may have been omitted. For example, separating the private-label purchase risk into components could provide new insights. The basic conclusions are strong. During the 7-year period that included the pandemic, shopping list use appears to have declined, private labels continue to be perceived as risky purchases, and self-checkout acceptance has increased. Many of the relationships identified with the 2015 data continued to be significant. Food marketers and retailers can use these results in their marketing.

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