Competitive Model Selection in Algorithmic Targeting[*]

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Abstract

This paper studies how market competition influences firms' algorithm design in the context of targeting. Firms face the general trade-off between bias and variance when choosing the design of a supervised learning algorithm in terms of model complexity or the number of predictors to accommodate. Each firm then appoints a data analyst that uses the chosen algorithm to estimate demand for multiple consumer segments, based on which, it devises a targeting policy to maximize estimated profit. We show that competition may induce firms to choose simpler algorithms with more biases. This implies that more complex/flexible algorithms tend to be more valuable to firms with greater monopoly power.

Keywords: *algorithmic competition, model selection, algorithmic bias, data analytics, targeting*

1 Introduction

The digital economy has made available unparalleled amounts of consumer data to firms. Over the past decade firms are increasingly delegating many business decisions, such as pricing, advertising and targeting, to artificial intelligence (AI) algorithms, which utilize large amounts of data on consumer characteristics and behaviors. One of the defining characteristics of big data environments is the rich and high dimensional information on consumer characteristics, attitudes, opinions and behaviors. Often the number of variables and aspects of consumer behaviors that is present can be comparable to the size of the dataset. Consequently, the big-data environment might confront the firms with the classic over-fitting problem in statistical learning: the algorithm may use a large number of available consumer predictors and complex functions to map the data onto predictions on consumer behaviors, but this increases the variance of the estimated predictions and thus reduces out-of-sample prediction precision. Alternatively, the algorithm can be regularized wherein the complex functions can be penalized leading to the selection of only the most relevant variables. This would reduce the variance of the estimated predictions but then may introduce biases in the estimates and thus compromise prediction accuracy. This is the general bias-variance tradeoff that underlies the design of any supervised learning algorithm. Our goal in this paper is to reexamine this tradeoff under a competitive setting.

Particularly, we first recognize that the primary job of an AI algorithm is to make predictions (Agrawal et al. 2018), and the primary reason for a user of an algorithm to make predictions is to facilitate decision making. Take self-driving cars as an example. The pattern recognition algorithms are used to predict whether an object is a pedestrian, a traffic light or a car, etc., the purpose of which is to help the car decide whether to proceed or make a stop. While many engineering applications such as the self-driving cars feature single decision makers' problems, in most economics and business settings, the user of an algorithm is rarely the only decision maker in the market. Consequently, market competition will affect the users' decision making, which in turn has further implications for their choice of the algorithm designs, because the decisions are based on the predictions that are made by the algorithms.

These considerations motivate us to study how market competition influences firms' algorithm design which trades off bias and variance in model selection. We choose the specific context of targeting (or targeted advertising) to study the problem of "competitive model selection", because targeting has been one of the most prominent business applications of AI algorithms that leverage big data on consumers. Consistent with common industry practices, we model firms' algorithmic decision making process as involving two steps. First, a firm chooses an algorithm design in terms of a statistical model and fits the model with data. Second, it makes targeting decisions based on the model estimates under the market competition. This setup ensures that the firms' choices of algorithm designs will have an active impact on their strategic decisions on targeting. On the other hand, it also implies that our modelling choice will inevitably depart from a standard Bayesian approach, because for Bayesian decision makers, data are informative signals that always update their belief by Bayes' rule, and consequently, there is no active role an algorithm design could play. To avoid the inconsistency with a Bayesian approach, we rationalize our algorithmic decision making process by considering delegation of a firm's data analytics process to an analyst under an incomplete contract. In other words, we view a data analytics algorithm as one way to representing consumer data for the firms' decision making so that different algorithm designs amount to different representations of consumer information, which induces the firms to make different decisions.

We operationalize the firms' algorithm design problem of model selection by a popular supervised learning algorithm—the Lasso regression, which selects variables via penalization on variable coefficients so as to enhance the prediction accuracy and model interpretability. The Lasso regression is a natural choice for our purpose because the bias-variance tradeoff is directly modulated by the degree of penalization, or the choice of a hyperparameter. Moreover, it is simple enough to allow for analytical tractability while flexible enough for practical usage.

To be more specific, we consider a duopoly market in which two firms compete by targeting consumers who are heterogeneous in some characteristic. Targeting is costly and acts as a form of informative advertising (Butters 1977). Firms observe consumer characteristics from their data but are uncertain about the profitability of different consumer types, something they are interested to estimate via data analytics. Given the specialized expertise needed to deploy predictive algorithms, the firms delegate the task of data analytics to a data analyst, who is equipped with the technology of running Lasso regressions. Meanwhile, the firms retain the strategic choice of the hyperparameters, which determine the complexity of the algorithms. Lastly, based on the model estimates reported by one's analyst, each firm chooses the targeting strategy to maximize estimated profit.

We first analyze the monopoly benchmark and show that it is optimal for the firm to choose zero penalization. In other words, a monopoly firm prefers a more complex or flexible algorithm design which admits more variance but has lower bias. This enables the firm to achieve greater market coverage in the sense that it allows it to target the more profitable consumer segment with greater likelihood. Then, we proceed to analyze the competitive market and find that in equilibrium, at least one firm will choose positive penalization which introduces bias while reducing variance by selecting fewer variables for making predictions. In other words, competition favors simpler models for targeting in equilibrium. The general intuition is that under competition, the firms have two incentives: i) to correctly target the more profitable segment, and ii) to avoid competition and the overlap in targeting. Simpler models lead to more uniform targeting, which helps to reduce overlap and soften competition. Overall, the suggestion of our analysis is that more flexible and complex algorithms such as deep learning are likely to be of higher usage value to firms with greater monopoly power for targeting.

2 Related Research

Our paper is broadly related to the emerging research literature which examines strategic interactions and incentives with algorithms. One strand of research tackles the problem of algorithm design for a principal when faced with strategic agents who can manipulate the information that is provided to the algorithm. For example, Eliaz and Spiegler (2019) examines a statistical algorithm faced with an agent who strategically self-reports her personal data and highlights the role of model selection and the incentive-compatibility issues in truthful reporting that it creates for the agent. In a similar vein, Björkegren et al. (2020) considers individuals who may observe the rules of the machine learning algorithms and strategically manipulate their behavior to get desired outcomes. The paper derives an equilibrium estimator that is robust to manipulation given the costs of manipulating different behaviors. Our paper examines the model selection problem in a competitive market where firms choose the equilibrium design of their consumer targeting algorithms. Thus here the extent to which firms choose more or less flexible algorithms and the associated bias-variance trade-off is governed by the equilibrium consumer targeting incentives of competing firms.

There is a stream of research on competitive interactions between multiple algorithms. Salant and Cherry (2020) consider statistical inference in games, where each player obtains a small random sample of other players' actions, uses statistical inference to estimate their actions, and chooses an optimal action based on the estimate. Liang (2020) considers games of incomplete information in which the players have data and use algorithms to derive their beliefs. Olea et al. (2019) study a game between agents competing to predict a common variable, and where agents obtain the same data but differ in the algorithms they utilize for prediction. In all these papers, the algorithms under consideration are fixed exogenously. Here, in contrast, we focus on the strategic choice of algorithms in competitive environments.

There is also recent research on how algorithmic decision making affects market competition, a question complementary to ours. For example, Miklós-Thal and Tucker (2019) model the effect of AI algorithms as better demand forecasting and show that algorithms could impede tacit price collusion. Calvano et al. (2020) examine firms endowed with Q-learning algorithms in repeated interactions to show that they can robustly learn to cooperate to charge supra-competitive prices without communicating with each other. Lastly, we contribute to the traditional literature on competitive targeting strategies (e.g., Shaffer and Zhang 1995; Chen et al. 2001; Iyer et al. 2005; Bergemann and Bonatti 2011) by introducing the algorithm design and decisions on model selection to the consumer targeting strategies of firms.[1]

3 Model Setup

Consider a market consisting of consumers who are heterogeneous in a characteristic $x \in \{1, 0\}$. A fraction ϕ of consumers have $x = 1$ and the remaining $1 - \phi$ fraction have $x = 0$, where $\phi \in (0, 1)$. For example, x_i may represent consumer i's demographics (1 for men and 0 for women), or past consumer behaviors (1 for those who have visited some website and 0 otherwise), etc. This case of a single characteristic offers the simplest setup for the development of the idea.

There are two firms competing for consumers in the market, indexed by $j = 1, 2$. Firms can observe each consumer i's characteristic x_i and decide which type(s) of consumers to target. Each firm has the ability to reach and target $\theta \in (0, 1)$ fraction of the consumer population in the market. Targeting can therefore be also interpreted as a form of costly informative advertising that informs consumers of the existence of the product (Butters 1977). If consumer i is only targeted by firm j, the consumer will only buy from the firm, and the firm earns a monopolistic profit of $\pi_j(x_i)$; on the other hand, if the consumer is targeted by both firms, she will randomly choose a firm to make a purchase, and thus firm j's expected profit is $\pi_j(x_i)/2$. Lastly, if a consumer is not targeted by either of the two firms, she will not make a purchase from the two firms. To focus the exposition on the effects of algorithmic targeting, we have abstracted away

[1] Algorithmic targeting has also been the focus of several recent empirical studies (e.g., Hitsch and Misra 2018; Simester et al. 2020; Rafieian and Yoganarasimhan 2021).

the firms' decisions on prices.[2]

Given that x is binary, it is without loss of generality to write down $\pi_j(x)$ as the following linear function,

$$\pi_j(x) = \alpha_j + \beta_j x.$$

Firm j does not know α_j, β_j a priori. We assume a common prior for α_j, β_j, which follow differentiable distribution functions A and B respectively. A is supported in $[\underline{\alpha}, \overline{\alpha}]$, and B is a symmetric distribution around zero, supported in $[-\overline{\beta}, \overline{\beta}]$. α_1, β_1, α_2 and β_2 are independently distributed. The firm is interested in estimating α_j and β_j given the available data. It delegates the task of estimation and prediction to a data analyst which is equipped with the technology of running prediction and model selection algorithms.[3] Specifically, assume that the analyst uses the technology of running Lasso regressions and that a complete contract between the firm and the data analyst is not possible. Rather, the firm can only specify the tuning parameter of the Lasso regression. Given the tuning parameter specified by the firm, the analyst runs the Lasso regression on the data to generate an estimate of α_j and β_j.

It is assumed that each firm j and its data analyst have a private access to a data-set with two observations. The l-th observation contains a pair of (x^l, y_j^l) for $l = 0, 1$, where, $x^0 = 0$, $x^1 = 1$ and

$$y_j^l = \pi_j(x^l) + \varepsilon_j^l = \alpha_j + \beta_j x^l + \varepsilon_j^l.$$

The error term, ε_j^l is i.i.d. across j and l and follows a differentiable distribution function G, which is symmetric around zero and supported in $[-\overline{\varepsilon}, \overline{\varepsilon}]$. Further define $\Delta\varepsilon_j \equiv \varepsilon_j^1 - \varepsilon_j^0$, which follows distribution function $\widetilde{G}$, where $\widetilde{G}(e) = \Pr(\varepsilon_j^1 - \varepsilon_j^0 \leq e) = \int_{-\overline{\varepsilon}}^{\overline{\varepsilon}} G(e' + e) dG(e')$. We make the following assumption.

Assumption 1. *$\widetilde{G}'$ is single-peaked; that is, $\widetilde{G}'(e)$ weakly decreases (increases) with e for $e > 0$ ($e < 0$).*

Note that the data-set that each firm uses for targeting is assumed to be exogenous and independent of the ensuing market competition. One interpretation of this setup is

[2] If price discrimination based on targeting outcomes is allowed, we may endogenize prices in a trivial way. If a consumer is targeted by only one firm, the firm sets the monopoly price and still earns a monopoly profit; on the other hand, if a consumer is targeted by two firms, they engage in a Bertrand competition, which drives the price to be the marginal cost and each firm's profit to be zero. This setting will generate qualitatively the same result as in the model without explicit consideration of prices.

[3] One can imagine the "firm" to be a senior data scientist who decides the architecture design of the algorithms including the choice of the programming language, libraries as well as the modeling approaches, while the "data analyst"'s main responsibility is to implement the chosen algorithms.

that either the two firms are new to the market, or that they have recently adopted the data analytics technology, such that before a full-blown implementation, each of them has experimented/test-marketed the technology in some sub-markets such as different geographic regions or sales channels that do not overlap. This would generate a "monopolistic" private data-set for each firm. In Section 6, we will describe an alternative setting in which the data-set results from market competition, and argue that it would nevertheless generate results that are qualitatively similar to that in the main model.

Based on the data, the analyst runs a Lasso regression, which is represented by the following minimization problem:

$$\left(\hat{\alpha}_j(\lambda_j), \hat{\beta}_j(\lambda_j)\right) = \underset{(a_j, b_j)}{\arg\min} \sum_{l=0}^{1} \left(y_j^l - a_j - b_j x^l\right)^2 + \lambda_j |b_j|, \tag{1}$$

where $\lambda_j \geq 0$ is the tuning parameter specified by firm j that measures the degree of penalization on $\hat{\beta}_j(\lambda_j)$. The choice of λ_j indicates the model selection decision of the firm: At the one extreme when $\lambda_j = 0$, this corresponds to the case of a standard ordinary least square (OLS) regression and in this setup this is equivalent to the firm deciding on the maximum model flexibility and choosing all the available predictor variables. This will imply estimated parameters which are unbiased but which will have maximum variance. In contrast, when λ_j is large and the penalization is large, then the model would shrink and have lower flexibility with fewer admitted predictors. In this case the variance of the estimated parameters would be lowered but at the cost of introducing bias.

From the corresponding first- and second-order optimality conditions, we can solve the data analyst's estimation problem in equation (1):

$$\hat{\alpha}_j(\lambda_j) = \frac{1}{2}\left(y_j^1 + y_j^0 - \hat{\beta}_j(\lambda_j)\right), \tag{2}$$

$$\hat{\beta}_j(\lambda_j) = \begin{cases} \max\{y_j^1 - y_j^0 - \lambda_j, 0\}, & \text{if } y_j^1 - y_j^0 \geq 0, \\ \min\{y_j^1 - y_j^0 + \lambda_j, 0\}, & \text{otherwise.} \end{cases} . \tag{3}$$

The expression of $\hat{\alpha}_j(\lambda_j)$ in equation (2) is the same as the standard OLS estimator, because there is no penalization on $\hat{\alpha}_j(\lambda_j)$. It is assumed that $\underline{\alpha}$ is large enough so that the realization of $\hat{\alpha}_j(\lambda_j)$ is always positive for any $\lambda_j \geq 0$. Formally,

Assumption 2. $\underline{\alpha} > \overline{\beta}/2 + \overline{\varepsilon}$.

This guarantees that firm j always prefers to target as many consumers as possible in the market. That is, the constraint of a total number of θ consumers to target will always be binding so that the firm's targeting decision boils down to which type(s) of consumers to target. To understand the expression of $\hat{\beta}_j(\lambda_j)$ intuitively, notice that if $\lambda_j = 0$, we have $\hat{\beta}_j(\lambda) = y_j^1 - y_j^0$, which is the OLS estimator. When $0 < \lambda_j < |y_j^1 - y_j^0|$, then $\hat{\beta}_j(\lambda_j)$ will have the same sign with $y_j^1 - y_j^0$ but is penalized toward zero. Finally, if $\lambda_j \geq |y_j^1 - y_j^0|$, the penalization is so severe that $\hat{\beta}_j(\lambda_j) = 0$.

We consider a simultaneous-move game between the two firms in two periods. First, each firm j chooses the tuning parameter λ_j, which remains private for the entire game. Second, each firm j is endowed with a private data-set (x^l, y_j^l) for $l = 0, 1$, based on which, firm j's analyst generates the estimates $\hat{\alpha}_j(\lambda_j)$ and $\hat{\beta}_j(\lambda_j)$ by running a Lasso regression. Lastly, each firm devises the targeting strategy to maximize the estimated profit. Figure 1 summarizes the timeline of the game. Before we proceed to analyze the game, we elaborate on the rationale and interpretation of our modeling choices.

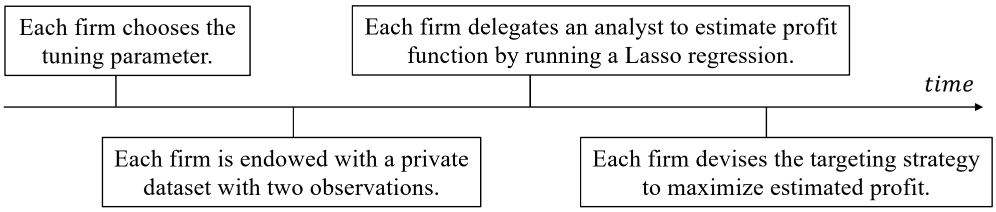


Figure 1: Timeline of the competitive algorithmic targeting game.

First, the reader may wonder that the simple setup above with a data set of just two observations and a binary characteristic ($x \in (1, 0)$) is a far cry from the big data situations confronting firms. Machine learning models are typically high dimensional and complex involving numerous dimensions available in big data. Nevertheless, as also previously argued by Eliaz and Spiegler (2019) the setup is designed to handle the crucial aspects of the "over-fitting" problem encountered in algorithmic decision making by firms, namely, that the potential number of explanatory variables may be large and comparable to the sample size. So unless there is a method for model selection and shrinkage of the number of explanatory variables there is a risk of over-fitting. For example, an unpenalized regression estimator may perfectly fit the data-set but would have high variance and poor predictive performance compared to an estimator with shrinkage. However, a model with shrinkage may be subject to the introduction of bias in the estimated coefficients. The model with the Lasso regression with the endogenous choice of the tuning parameter λ_j helps to capture the essence of the trade-offs underlying the over-fitting problem, and in doing so, it endogenizes the model selection to the equilibrium incentives of the firms.

Second, the firms choose the tuning parameters before getting the data. This may also be seen as consistent with the statistical learning literature which prescribes that the tuning parameter should not be determined based on the training data per se in order to avoid over-fitting.

Third, while we use the Lasso regression as a specific estimation procedure, our results are more general in the sense that λ_j determines the general trade-off between bias and variance in any supervised learning method, where higher values of λ_j is associated with lower the variance but higher bias. Therefore, firm j's choice of λ_j can be interpreted as choosing between different statistical learning models that differ in bias-variance trade-off. Thus the problem can be viewed as the strategic choice of the bias-variance trade-off in algorithm design of the firm's targeted advertising strategy.

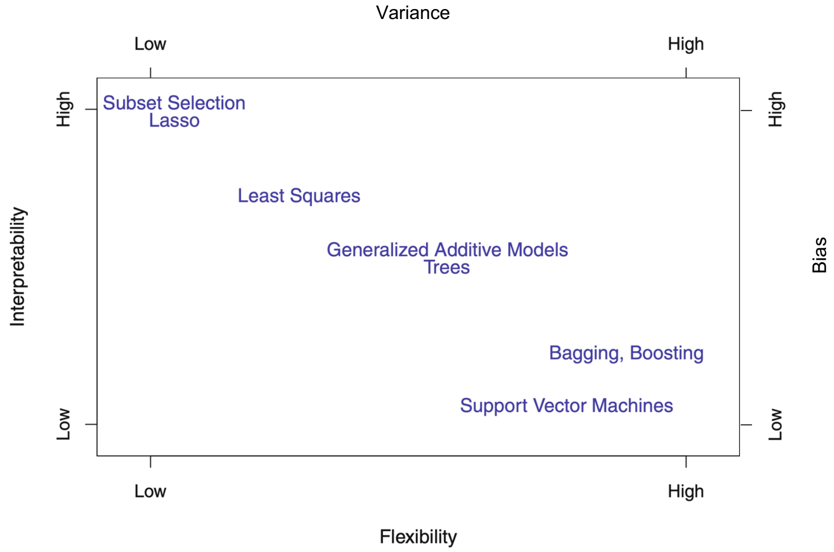


Figure 2: Tradeoff between flexibility and interpretability and tradeoff between bias and variance across different statistical learning methods (excerpted from James et al. (2013) page 25 and adapted).

Furthermore, different statistical models differ in their flexibility and their degree of interpretability, as shown by Figure 2. Typically, those with higher flexibility (and lower interpretability) have lower bias but higher variance. Here we will focus on the comparison between Lasso and OLS, where OLS has higher flexibility and lower bias, while Lasso with some level of regularization has lower flexibility and higher bias and may be more easily interpretable when compared to OLS. Therefore, the choice of λ_j may also represent the relative complexity versus interpretability of the algorithm. Also by this understanding, the Lasso regression does not necessarily need to represent a "machine-learning" algorithm while OLS a traditional algorithm. In fact, in practice, a firm may decide whether to adopt a very flexible machine-learning algorithm like neural networks compared with a less flexible benchmark algorithm, in which case, the neural networks will correspond to OLS in our framework.

Finally, it has been assumed that the firms do not have the analytical capability themselves and rely on data analysts for the estimation procedure; moreover complete contracts are not available between a firm and its analyst. This assumption maps onto common practices in companies where managers rely on analysis by data analytics groups to make strategic decisions. This has two important implications:

1. In the last stage of the game, instead of performing a Bayesian update based on the data to calculate the posterior belief of α_j and β_j, each firm relies on the data analyst to run the Lasso regression on the data to get point estimates of $\hat{\alpha}_j(\lambda_j)$ and $\hat{\beta}_j(\lambda_j)$; correspondingly, instead of maximizing the expected profit based on the posterior belief, each firm makes the targeting decision by maximizing the "estimated profit" based on the estimate, $\hat{\alpha}_j(\lambda_j)$ and $\hat{\beta}_j(\lambda_j)$. The standard rational economic model for this problem would involve fully Bayesian decision making with common priors for all agents. However, as argued below the reality of data based algorithmic decision making in firms does not reconcile with the standard approach as machine learning algorithms like Lasso which are based on the minimization as in (1) are non-bayesian procedures. By separating the estimation problems from the decision-maker (firms), and delegating it to agents (analysts), we are able to rationalize the reality of data-driven decision making in firms. Methodologically this feature of our framework is a representation of algorithmic decision making in firms.[4]

2. Because it is the data analyst instead of the firm that performs the estimation procedure, this implies the minimization of mean squared error instead of profit maximization as the objective in estimating the parameters in the second stage. This makes our results directly comparable with the standard statistical learning literature. This is also consistent with the industry practice due to several consid-

[4]In an alternative setting in absence of the data analysts, we can assign a Laplace prior distribution to each firm j's prior belief of β_j, with the probability density function $f(\beta_j) = \lambda_j/2 \cdot \exp(-\lambda_j|\beta_j|)$. Then, based on the data (x^l, y_j^l) for $l = 0, 1$ and assuming ε_j^l follows a standard normal distribution, firm j forms a posterior belief of α_j and β_j by Bayes' rule, which can be shown to be equivalent to running the Lasso regression in equation (1) (Tibshirani 1996). However, there are two caveats to this Bayesian approach. First, the tuning parameter λ_j is not firm j's choice but rather, a model primitive that is exogenously given. To endogenize the firm's choice of λ_j would be equivalent to let the firm choose its prior distribution. Second, the point estimates generated by the Lasso regression, $\hat{\alpha}(\lambda_j)$ and $\hat{\beta}(\lambda_j)$ in equations (2) and (3) are mode instead of mean of the posterior belief of α_j and β_j (Hastie et al. 2009). However, to calculate expected profit, we will be mostly concerned with the posterior mean instead of the mode.

erations. First, minimization of mean squared error is available and used by companies in standard ready-to-use statistical packages while profit maximization requires customization, which could be costly for the firms. Second, information pertaining to the profit function may be scattered in silos within the organization so that even if the data analyst in charge of the estimation task wants to use profit maximization as the objective, she may fail to gather all relevant information.

We begin with the analysis of the monopoly setting with only one firm in the market as the benchmark, and then proceed to study the main model with competition.

4 Monopoly Benchmark

Given only one firm, we will drop the subscript j. We solve the game by backward induction. Suppose the firm decides to target $k \in [0, \phi]$ consumers with $x = 1$ and $\theta - k \in [0, 1 - \phi]$ consumers with $x = 0$, which imply that

$$\max\{0, \theta + \phi - 1\} \leq k \leq \min\{\theta, \phi\}.$$

Given $\hat{\alpha}(\lambda)$ and $\hat{\beta}(\lambda)$, we have the estimated profit from a targeted consumer to be $\hat{\pi}(x) = \hat{\alpha}(\lambda) + \hat{\beta}(\lambda)x$. The firm chooses k to maximize the estimated profit. If $\hat{\beta}(\lambda) > 0$, it is optimal for the firm to target as many consumers with $x = 1$ as possible, so we have the firm's optimal choice of k as $k^* = \min\{\theta, \phi\}$. Similarly, if $\hat{\beta}(\lambda) < 0$, it is optimal for to target as many consumers with $x = 0$ as possible, and thus, $k^* = \max\{0, \theta + \phi - 1\}$. Lastly, if $\hat{\beta}(\lambda) = 0$, the firm is indifferent between the two types of consumers, and it is assumed that it will target $k \in [0, \theta]$ consumers with $x = 1$.

A priori, before obtaining the dataset, the firm chooses λ to maximize the expected profit from all consumers:

$$\begin{aligned}
\Pi(\lambda) =& \mathrm{E}[\theta\alpha + k^*\beta] \\
=& \theta\mathrm{E}[\alpha] + \min\{\theta, \phi\} \Pr(\hat{\beta}(\lambda) > 0)\mathrm{E}[\beta | \hat{\beta}(\lambda) > 0] \\
& + \max\{\theta - (1 - \phi), 0\} \Pr(\hat{\beta}(\lambda) < 0)\mathrm{E}[\beta | \hat{\beta}(\lambda) < 0] \\
& + k \Pr(\hat{\beta}(\lambda) = 0)\mathrm{E}[\beta | \hat{\beta}(\lambda) = 0] \\
=& \theta\mathrm{E}[\alpha] + \min\{\theta, \phi\} \Pr(\beta + \Delta\varepsilon > \lambda)\mathrm{E}[\beta | \beta + \Delta\varepsilon > \lambda] \\
& + \max\{\theta - (1 - \phi), 0\} \Pr(\beta + \Delta\varepsilon < -\lambda)\mathrm{E}[\beta | \beta + \Delta\varepsilon < -\lambda] \\
=& \theta\mathrm{E}[\alpha] + \min\{\theta, \phi\} \int_{-2\overline{\varepsilon}}^{2\overline{\varepsilon}} d\widetilde{G}(e) \int_{\lambda - e}^{\overline{\beta}} b dB(b)
\end{aligned}$$

$$
\begin{aligned}
&+\max\{\theta-(1-\phi),0\}\int_{-2\overline{\varepsilon}}^{2\overline{\varepsilon}} d\widetilde{G}(e)\int_{-\overline{\beta}}^{-\lambda-e} bdB(b)\\
=&\theta\mathrm{E}[\alpha]+\min\{\theta,1-\theta,\phi,1-\phi\}\int_{-2\overline{\varepsilon}}^{2\overline{\varepsilon}} d\widetilde{G}(e)\int_{\lambda-e}^{\overline{\beta}} bdB(b).
\end{aligned}
$$

To get the third equation above, notice that $\hat{\beta}(\lambda) > 0 \Leftrightarrow \beta + \Delta\varepsilon > \lambda$, $\hat{\beta}(\lambda) < 0 \Leftrightarrow \beta + \Delta\varepsilon < -\lambda$, and $\hat{\beta}(\lambda) = 0 \Leftrightarrow |\beta + \Delta\varepsilon| \leq \lambda$, which, combining with the fact that B and $\widetilde{G}$ are symmetric distributions around zero, further implies that $\mathrm{E}[\beta|\hat{\beta}(\lambda) = 0] = \mathrm{E}[\beta||\beta + \Delta\varepsilon| \leq \lambda] = 0$. Therefore, the choice of k has no impact on firm profit and thus the tie-breaking rule has no bite on the result. To get the last equation, we have again utilized the symmetry of $\widetilde{G}$ and B.

Given $\widetilde{G}'$ is single-peaked, one can show that $\Pi(\lambda)$ decreases with λ, so we have the following proposition.

Proposition 1. *Under monopoly, the firm chooses the tuning parameter* $\lambda^M = 0$.

Proof.

$$
\Pi'(\lambda) = -\min\{\theta, 1-\theta, \phi, 1-\phi\}\int_{-2\overline{\varepsilon}}^{2\overline{\varepsilon}} (\lambda - e)B'(\lambda - e)\widetilde{G}'(e)de.
$$

If $\lambda \geq 2\overline{\varepsilon}$, obviously, $\Pi'(\lambda) \leq 0$. Otherwise, if $\lambda < 2\overline{\varepsilon}$, we have

$$
\begin{aligned}
\Pi'(\lambda) \propto& -\left(\int_{-2\overline{\varepsilon}}^{2\lambda-2\overline{\varepsilon}} + \int_{2\lambda-2\overline{\varepsilon}}^{\lambda} + \int_{\lambda}^{2\overline{\varepsilon}}\right)(\lambda - e)B'(\lambda - e)\widetilde{G}'(e)de\\
=& -\int_{-2\overline{\varepsilon}}^{2\lambda-2\overline{\varepsilon}} (\lambda - e)B'(\lambda - e)\widetilde{G}'(e)de - \theta\int_{0}^{2\overline{\varepsilon}-\lambda} zB'(z)\left(\widetilde{G}'(\lambda - z) - \widetilde{G}'(\lambda + z)\right)dz\\
\leq& \, 0,
\end{aligned}
$$

where, to get the second equality above, we have changed the variable $e = \lambda - z$ for the second integral from $2\lambda - 2\overline{\varepsilon}$ to λ, and $e = \lambda + z$ for the third integral from λ to $2\overline{\varepsilon}$; moreover, we have utilized $B'(z) = B'(-z)$. To get the last inequality, notice that given $\widetilde{G}'$ being single-peaked and symmetric around zero, we have $\widetilde{G}'(\lambda - z) \geq \widetilde{G}'(\lambda + z)$ for any $z \geq 0$ and $\lambda \geq 0$. To summarize, we have shown that $\Pi'(\lambda) \leq 0$, so the optimal λ should be $\lambda^M = 0$. □

Proposition 1 implies that a monopoly firm in this setup prefers the OLS regression to a Lasso. The intuition is that the OLS estimator is unbiased and thus enables the firm to target the more profitable segment correctly in expectation. The qualitative implication is that a monopolist optimally prefers a more flexible or complex algorithm design which accommodates all the variables (in our case one) and which may risk over-fitting the data. In other words, the monopoly prefers low algorithmic bias but this would come at the expense of increased variance. This result serves as benchmark and motivates our analysis below of the competitive incentives for algorithmic targeting.

5 Competitive Targeting

Now we analyze the main model with competition between two firms and solve for the equilibrium by backward induction.

5.1 Targeting Decision

Given firm j's choice of the tuning parameter as λ_j and its private data-set, the firm's analyst's estimates, $\hat{\alpha}(\lambda_j)$ and $\hat{\beta}(\lambda_j)$ are given by equation (3). Suppose firm j decides to target k_j consumers with $x = 1$ and $\theta - k_j$ consumers with $x = 0$ for $j = 1, 2$. Similarly, we have $\max\{0, \theta + \phi - 1\} \le k_j \le \min\{\theta, \phi\}$.

Firm j does not observe the rival's choice of the tuning parameter nor its dataset. Denote firm j's expectation of the other firm's choice of the tuning parameter as λ^*_{-j}. Furthermore, from firm j's perspective, the other firm's equilibrium choice of k^*_{-j} depends on the realization of its private dataset and thus is a random variable, which is denoted as $\widetilde{k}^*_{-j}$. Let's calculate firm j's estimated profit:

$$\begin{aligned}
\Pi_j(k_j, \widetilde{k}^*_{-j}) =& k_j \left(\frac{\widetilde{k}^*_{-j}}{\phi} \cdot \frac{1}{2} + 1 - \frac{\widetilde{k}^*_{-j}}{\phi} \right) \left(\hat{\alpha}_j(\lambda_j) + \hat{\beta}_j(\lambda_j) \right) \\
& + (\theta - k_j) \left(\frac{\theta - \widetilde{k}^*_{-j}}{1 - \phi} \cdot \frac{1}{2} + 1 - \frac{\theta - \widetilde{k}^*_{-j}}{1 - \phi} \right) \hat{\alpha}_j(\lambda_j) \\
=& \theta \left(1 - \frac{\theta - \widetilde{k}^*_{-j}}{2(1 - \phi)} \right) \hat{\alpha}_j(\lambda_j) \\
& + k_j \left(\frac{\phi\theta - \widetilde{k}^*_{-j}}{2\phi(1 - \phi)} \hat{\alpha}_j(\lambda_j) + \left(1 - \frac{\widetilde{k}^*_{-j}}{2\phi} \right) \hat{\beta}_j(\lambda_j) \right). \qquad (4)
\end{aligned}$$

To understand the first equation above, notice that firm j targets k_j consumers with $x = 1$, each of whom is also targeted by the other firm $-j$ with probability $\widetilde{k}^*_{-j}/\phi$. If this happens, firm j gets an estimated profit of $\left(\hat{\alpha}_j(\lambda_j) + \hat{\beta}_j(\lambda_j) \right)/2$; otherwise, with probability $1 - \widetilde{k}^*_{-j}/\phi$, this consumer is not targeted by firm $-j$, and firm j's estimated profit is $\left(\hat{\alpha}_j(\lambda_j) + \hat{\beta}_j(\lambda_j)\right)$. Similarly, we can perform the same calculation to get firm j's estimated profit from $\theta - k_j$ consumers with $x = 0$.

Firm j chooses $k_j \in [\max\{0, \theta + \phi - 1\}, \min\{\theta, \phi\}]$ to maximize the expected estimated profit, $\mathrm{E}\big[\Pi_j(k_j, \widetilde{k}^*_{-j})\big] = \Pi_j(k_j, \mathrm{E}[\widetilde{k}^*_{-j}])$, where we have utilized the observation that $\Pi_j(k_j, \widetilde{k}^*_{-j})$ is linear in $\widetilde{k}^*_{-j}$.[5] Furthermore, notice that $\Pi_j(k_j, \mathrm{E}[\widetilde{k}^*_{-j}])$ is linear in k_j with

$$\frac{\partial \Pi_j(k_j, \mathrm{E}[\widetilde{k}^*_{-j}])}{\partial k_j} = \underbrace{\frac{\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\hat{\alpha}_j(\lambda_j)}_{\text{to avoid competition}} + \underbrace{\left(1 - \frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\hat{\beta}_j(\lambda_j)}_{\text{to target the more profitable segment}} \equiv \eta_j(\lambda_j). \tag{5}$$

Consider the expression for $\partial_{k_j}\Pi_j(k_j, \mathrm{E}[\widetilde{k}^*_{-j}])$ in equation (5): The second term plays a similar role as the counterpart under the monopoly benchmark – the firm wants to target consumers with $x = 1$ when $\hat{\beta}_j(\lambda_j) > 0$, and $x = 0$ when $\hat{\beta}_j(\lambda_j) < 0$. The first term introduces incentives for the two firms to coordinate so as to avoid competition. Particularly, firm j wants to target consumers with $x = 1$ when $\mathrm{E}[\widetilde{k}^*_{-j}]/\theta < \phi$, that is, when the other firm would target proportionally more consumers with $x = 0$; similarly, firm j wants to target consumers with $x = 0$ when $\mathrm{E}[\widetilde{k}^*_{-j}]/\theta > \phi$, that is, when the other firm would target proportionally more consumers with $x = 1$.

$\Pi_j(k_j, \mathrm{E}[\widetilde{k}^*_{-j}])$ being linear in k_j immediately implies that the firm's optimal targeting decision takes corner solutions. Specifically, if $\eta_j(\lambda_j) > 0$, firm j should set $k^*_j = \min\{\theta, \phi\}$ to target as many consumers with $x = 1$ as possible; if $\eta_j(\lambda_j) < 0$, the firm should set $k^*_j = \max\{0, \theta + \phi - 1\}$ to target as many consumers with $x = 0$ as possible. Lastly, from an ex-ante perspective before the realization of firm j's private data-set, $\hat{\alpha}_j(\lambda_j)$ follows a continuous distribution and thus as long as $\mathrm{E}[\widetilde{k}^*_{-j}] \neq \phi\theta$, $\eta_j(\lambda_j) = 0$ is a knife-edge case that happens with zero probability; consequently, the tie-breaking rule for which consumer to target at $\eta_j(\lambda_j) = 0$ has no consequence. On the other hand, if $\mathrm{E}[\widetilde{k}^*_{-j}] = \phi\theta$, we have $\eta_j(\lambda_j) = 0 \Leftrightarrow \hat{\beta}_j(\lambda_j) = 0$, at which, we have shown for the monopoly case above, the tie-breaking rule has no consequence either.

[5] Notice that as α_1, β_1, α_2 and β_2 are independently distributed, firm j's private dataset provides no information on α_{-j} and β_{-j}. Therefore, $\mathrm{E}[\widetilde{k}^*_{-j}|\text{firm } j\text{'s dataset}] = \mathrm{E}[\widetilde{k}^*_{-j}]$.

5.2 Model Selection

Let's first introduce the following notation. From firm, j's perspective, the probability that the other firm $-j$ will set $\widetilde{k}^*_{-j} = \min\{\theta, \phi\}$ is:

$$
\begin{aligned}
p_{-j} \equiv & \Pr\left(\widetilde{k}^*_{-j} = \min\{\theta,\phi\}\right) \\
= & \Pr\left(\frac{\phi\theta - \mathrm{E}[\widetilde{k}^*_j]}{2\phi(1-\phi)}\hat{\alpha}_{-j}(\lambda^*_{-j}) + \left(1 - \frac{\mathrm{E}[\widetilde{k}^*_j]}{2\phi}\right)\hat{\beta}_{-j}(\lambda^*_{-j}) > 0\right) \\
= & \Pr\left(\frac{\phi\theta - (\max\{0,\theta+\phi-1\} + p_j\min\{\theta,1-\theta,\phi,1-\phi\})}{2\phi(1-\phi)}\hat{\alpha}_{-j}(\lambda^*_{-j})\right. \\
& \left. + \left(1 - \frac{\max\{0,\theta+\phi-1\} + p_j\min\{\theta,1-\theta,\phi,1-\phi\}}{2\phi}\right)\hat{\beta}_{-j}(\lambda^*_{-j}) > 0\right), \quad (6)
\end{aligned}
$$

where, to get the last equality in (6), we have utilized that

$$
\begin{aligned}
\mathrm{E}[\widetilde{k}^*_j] &= p_j\min\{\theta,\phi\} + (1-p_j)\max\{0,\theta+\phi-1\} \\
&= \max\{0,\theta+\phi-1\} + p_j\min\{\theta,1-\theta,\phi,1-\phi\},
\end{aligned}
$$

which is firm j's expectation of firm $-j$'s expectation of firm j's equilibrium choice of k^*_j, and thus $\mathrm{E}[\widetilde{k}^*_j]$ depends on λ^*_j (via p_j) instead of λ_j. By combining equation (6) for $j = 1, 2$, we should be able to solve p_1 and p_2, which depend on λ^*_1 and λ^*_2 (but not on λ_1 or λ_2).

Next, we determine λ^*_j by calculating firm j's expected profit before obtaining the private data-set, which takes the same form as the firm's estimated profit $\Pi_j(k^*_j, \widetilde{k}^*_{-j})$ in equation (4) except that we need to replace $\hat{\alpha}_j(\lambda_j)$ and $\hat{\beta}_j(\lambda_j)$ by α_j and β_j respectively and then take expectation.

$$
\begin{aligned}
\Pi_j(\lambda_j) \equiv & \mathrm{E}\left[\theta\left(1 - \frac{\theta - \widetilde{k}^*_{-j}}{2(1-\phi)}\right)\alpha_j + k^*_j\left(\frac{\phi\theta - \widetilde{k}^*_{-j}}{2\phi(1-\phi)}\alpha_j + \left(1 - \frac{\widetilde{k}^*_{-j}}{2\phi}\right)\beta_j\right)\right] \\
= & \theta\left(1 - \frac{\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}{2(1-\phi)}\right)\mathrm{E}[\alpha_j] \\
& + \min\{\theta,\phi\}\Pr\left(\eta_j(\lambda_j) > 0\right)\mathrm{E}\left[\frac{\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\alpha_j + \left(1 - \frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j \middle| \eta_j(\lambda_j) > 0\right]
\end{aligned}
$$

$$+\max\{0,\theta+\phi-1\}\Pr(\eta_j(\lambda_j)<0)\,\mathrm{E}\left[\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\alpha_j+\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j\middle|\eta_j(\lambda_j)<0\right]. \tag{7}$$

In the calculation, we have utilized the independence between α_j, β_j and $\widetilde{k}^*_{-j}$. $\Pi_j(\lambda_j)$ depends on λ_j via $\eta_j(\lambda_j)$ and depends on λ^*_{-j} via $\widetilde{k}^*_{-j}$. That is, at the model selection stage, firm j has an expectation of firm $-j$'s choice of the tuning parameter, λ^*_{-j}, which will influence firm $-j$'s targeting decision and thus in turn influences firm j's expected profit. In expectation, each firm's choice should be consistent with the other firm's expectation:

$$\lambda^*_j=\arg\max_{\lambda_j}\Pi_j(\lambda_j),\ \text{for } j=1,2. \tag{8}$$

To summarize, the equilibrium will be pinned down by the two sets of equations (6) and (8), where we have four equations to determine four variables: p_1, p_2, λ^*_1 and λ^*_2. The main result of this paper is presented next.

5.3 Main Result

Proposition 2. *If a pure-strategy equilibrium exists, $\phi\neq 1/2$, $\theta\neq 1/2$, and $\bar{\varepsilon}$ is sufficiently high, then, we must have $\lambda^*_j>0$ for at least one of $j=1,2$.*

Proposition 2 does not provide an explicit condition on when a pure-strategy equilibrium exists, which would require additional assumptions on distribution functions, A, B and G to ensure firm j's profit function, $\Pi_j(\lambda_j)$ is quasi-concave for $j=1,2$. Nevertheless, notice that if pure-strategy equilibria do not exist, Nash's celebrated theorem immediately implies that there must exist a mixed-strategy equilibrium, where trivially, we must have $\Pr(\lambda^*_j>0)>0$ for at least one of $j=1,2$ (otherwise, we have $\lambda^*_j=0$ for $j=1,2$, which is not a mixed-strategy equilibrium). Therefore, even if a pure-strategy equilibrium does not exist, we will end up with a result that is qualitatively similar in spirit with Proposition 2. Let's prove Proposition 2 next. Without loss of generality it is assumed that $\phi\in(0,1/2)$. The other case with $\phi\in(1/2,1)$ can be obtained by symmetry.

Proof. Let's first argue that given any λ^*_1 and λ^*_2, there must exist a solution of (p_1,p_2) to equation (6) for $j=1,2$. In fact, the right-hand side of equation (6) for $j=1,2$ is a continuous map on a convex compact set $[0,1]^2$ to itself, and by Brouwer fixed-point theorem, a fixed point must exist. Next, we calculate $\Pi_j(\lambda_j)$ in equation (7). There are three cases to consider.

(i) $\mathrm{E}[\widetilde{k}^*_{-j}] < \phi\theta$, given which, there are two observations. First, Assumption 2 implies that $\hat{\alpha}_j(\lambda_j) > 0$. This further implies that if $\hat{\beta}_j(\lambda_j) \geq 0$, we must have $\eta_j(\lambda_j) > 0$ by the definition of $\eta_j(\lambda_j)$ in equation (5). Second, $\hat{\beta}_j(\lambda_j) < 0$ implies that $\hat{\beta}_j(\lambda_j) = \beta_j + \Delta\varepsilon_j + \lambda_j$ and $\hat{\alpha}_j(\lambda_j) = \alpha_j + \varepsilon_j^0 - \lambda_j/2$ by equations (2) and (3), based on which, we have

$$\begin{aligned}
\eta_j(\lambda_j) < 0 \Leftrightarrow \alpha_j < -C\lambda_j + F(\beta_j, \varepsilon_j^0, \varepsilon_j^1), \text{ where} \\
C \equiv \frac{2\phi(1-\phi)}{\left|\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]\right|}\left(1 - \frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi} - \frac{\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}{4\phi(1-\phi)}\right), \\
F(\beta_j, \varepsilon_j^0, \varepsilon_j^1) \equiv -\frac{(1-\phi)(2\phi - \mathrm{E}[\widetilde{k}^*_{-j}])}{\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}\left(\beta_j + \varepsilon_j^1 - \varepsilon_j^0\right) - \varepsilon_j^0.
\end{aligned}$$

C is well defined given $\mathrm{E}[\widetilde{k}^*_{-j}] \neq \phi\theta$. It is easy to show that

$$C > 0 \Leftrightarrow 1 - \frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi} - \frac{\phi\theta - \mathrm{E}[\widetilde{k}^*_{-j}]}{4\phi(1-\phi)} > 0 \Leftrightarrow (1-2\phi) + (1-\theta) + \mathrm{E}[\widetilde{k}^*_{-j}] > 0,$$

which always holds regardless of the comparison between $\mathrm{E}[\widetilde{k}^*_{-j}]$ and $\phi\theta$.

Putting the two observations above together, we have

$$\begin{aligned}
&\Pr\left(\eta_j(\lambda_j) < 0\right)\mathrm{E}\left[\alpha_j | \eta_j(\lambda_j) < 0\right] \\
&= \Pr\left(\eta_j(\lambda_j) < 0 \text{ and } \hat{\beta}_j(\lambda_j) < 0\right)\mathrm{E}\left[\alpha_j \middle| \eta_j(\lambda_j) < 0 \text{ and } \hat{\beta}_j(\lambda_j) < 0\right] \\
&\quad + \Pr\left(\eta_j(\lambda_j) < 0 \text{ and } \hat{\beta}_j(\lambda_j) \geq 0\right)\mathrm{E}\left[\alpha_j \middle| \eta_j(\lambda_j) < 0 \text{ and } \hat{\beta}_j(\lambda_j) \geq 0\right] \\
&= \Pr\left(\alpha_j < -C\lambda_j + F(\beta_j, \varepsilon_j^0, \varepsilon_j^1)\right)\mathrm{E}\left[\alpha_j | \alpha_j < -C\lambda_j + F(\beta_j, \varepsilon_j^0, \varepsilon_j^1)\right] \\
&= \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}}\int_{-\bar{\varepsilon}}^{\bar{\varepsilon}}\int_{-\bar{\beta}}^{\bar{\beta}}\int_{\underline{\alpha}}^{\min\left\{\max\left\{-C\lambda_j + F(\beta_j, \varepsilon_j^0, \varepsilon_j^1), \underline{\alpha}\right\}, \bar{\alpha}\right\}} \alpha_j dA(\alpha_j) dB(\beta_j) dG(\varepsilon_j^0) dG(\varepsilon_j^1),
\end{aligned}$$

where to get the first equality above, we have used the definition of conditional probabilities and the law of total probability. Moreover, we have argued $\Pr\left(\eta_j(\lambda_j) = 0\right) = 0$ above, which implies that,

$$\Pr\left(\eta_j(\lambda_j) > 0\right)\mathrm{E}[\alpha_j | \eta_j(\lambda_j) > 0] = \mathrm{E}[\alpha_j] - \Pr\left(\eta_j(\lambda_j) < 0\right)\mathrm{E}[\alpha_j | \eta_j(\lambda_j) < 0].$$

Similarly, we can write down the expressions for $\Pr(\eta_j(\lambda_j) > 0)\mathrm{E}[\beta_j | \eta_j(\lambda_j) > 0]$ and $\Pr(\eta_j(\lambda_j) < 0)\mathrm{E}[\beta_j | \eta_j(\lambda_j) < 0]$. By substituting these back to $\Pi_j(\lambda_j)$ in equation (7), we find:

$$
\begin{aligned}
\Pi_j(\lambda_j) =& \theta\left(1-\frac{\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2(1-\phi)}\right)\mathrm{E}[\alpha_j] \\
&+\min\{\theta,\phi\}\left(\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\mathrm{E}[\alpha_j]+\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\mathrm{E}[\beta_j]\right) \\
&-\min\{\theta,1-\theta,\phi,1-\phi\}\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\beta}}^{\overline{\beta}}\int_{\underline{\alpha}}^{\min\left\{\max\left\{-C\lambda_j+F(\beta_j,\varepsilon^0_j,\varepsilon^1_j),\underline{\alpha}\right\},\overline{\alpha}\right\}} \\
&\left(\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\alpha_j+\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j\right)dA(\alpha_j)dB(\beta_j)dG(\varepsilon^0_j)dG(\varepsilon^1_j).
\end{aligned}
$$

Let's compute the derivative of $\Pi_j(\lambda_j)$ at $\lambda_j = 0$:

$$
\begin{aligned}
\Pi'_j(0) =& \min\{\theta,1-\theta,\phi,1-\phi\}C \\
&\times\iiint_{\underline{\alpha}\le F(\beta_j,\varepsilon^0_j,\varepsilon^1_j)\le\overline{\alpha}}\left(\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}F(\beta_j,\varepsilon^0_j,\varepsilon^1_j)+\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j\right) \\
&\times A'(F(\beta_j,\varepsilon^0_j,\varepsilon^1_j))dB(\beta_j)dG(\varepsilon^0_j)dG(\varepsilon^1_j) \\
\ge& \min\{\theta,1-\theta,\phi,1-\phi\}C\left(\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\underline{\alpha}-\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\overline{\beta}\right) \\
&\times\iiint_{\underline{\alpha}\le F(\beta_j,\varepsilon^0_j,\varepsilon^1_j)\le\overline{\alpha}}A'(F(\beta_j,\varepsilon^0_j,\varepsilon^1_j))dB(\beta_j)dG(\varepsilon^0_j)dG(\varepsilon^1_j).
\end{aligned}
$$

When $\overline{\varepsilon}$ is sufficiently large, Assumption 2 implies that $\underline{\alpha}$ is sufficiently large so that

$$
\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\underline{\alpha}-\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\overline{\beta}>0;
$$

moreover, $F(\beta_j,\varepsilon^0_j,\varepsilon^1_j)$ by definition is symmetrically distributed around zero and when $\overline{\varepsilon}$ is sufficiently large, $\Pr(\underline{\alpha}\le F(\beta_j,\varepsilon^0_j,\varepsilon^1_j)\le\overline{\alpha})>0$. Therefore, we have $\Pi'_j(0)>0$, which implies that $\lambda^*_j>0$.

(ii) $\mathrm{E}[\widetilde{k}^*_{-j}]>\phi\theta$, given which, there are similarly two observations. First, $\hat{\beta}_j(\lambda_j)\le 0$ implies $\eta_j(\lambda_j)<0$. Second, $\hat{\beta}_j(\lambda_j)>0$ implies that $\hat{\beta}_j(\lambda_j)=\beta_j+\Delta\varepsilon_j-\lambda_j$ and $\hat{\alpha}_j(\lambda_j)=\alpha_j+\varepsilon^0_j+\lambda_j/2$ by equations (2) and (3), based on which, we have

$$
\eta_j(\lambda_j)>0\Leftrightarrow\alpha_j<-C\lambda_j+F(\beta_j,\varepsilon^0_j,\varepsilon^1_j),
$$

the same as that in case (i). Putting the two observations together, we have that

$$
\begin{aligned}
&\Pr\left(\eta_j(\lambda_j)>0\right)\mathrm{E}\left[\alpha_j|\eta_j(\lambda_j)>0\right]\\
&=\Pr\left(-C\lambda_j+F(\beta_j,\varepsilon_j^0,\varepsilon_j^1)\right)\mathrm{E}\left[\alpha_j\middle|-C\lambda_j+F(\beta_j,\varepsilon_j^0,\varepsilon_j^1)\right]\\
&=\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\beta}}^{\overline{\beta}}\int_{\underline{\alpha}}^{\min\left\{\max\left\{-C\lambda_j+F(\beta_j,\varepsilon_j^0,\varepsilon_j^1),\underline{\alpha}\right\},\overline{\alpha}\right\}}\alpha_j dA(\alpha_j)dB(\beta_j)dG(\varepsilon_j^0)dG(\varepsilon_j^1),\\
&\Pr\left(\eta_j(\lambda_j)<0\right)\mathrm{E}[\alpha_j|\eta_j(\lambda_j)<0]=\mathrm{E}[\alpha_j]-\Pr\left(\eta_j(\lambda_j)>0\right)\mathrm{E}[\alpha_j|\eta_j(\lambda_j)>0].
\end{aligned}
$$

Similarly, we can write down $\Pi_j(\lambda_j)$:

$$
\begin{aligned}
\Pi_j(\lambda_j)=&\theta\left(1-\frac{\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2(1-\phi)}\right)\mathrm{E}[\alpha_j]\\
&+\max\{0,\theta+\phi-1\}\left(\frac{\phi\theta-\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi(1-\phi)}\mathrm{E}[\alpha_j]+\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\mathrm{E}[\beta_j]\right)\\
&-\min\{\theta,1-\theta,\phi,1-\phi\}\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\varepsilon}}^{\overline{\varepsilon}}\int_{-\overline{\beta}}^{\overline{\beta}}\int_{\underline{\alpha}}^{\min\left\{\max\left\{-C\lambda_j+F(\beta_j,\varepsilon_j^0,\varepsilon_j^1),\underline{\alpha}\right\},\overline{\alpha}\right\}}\\
&\quad\left(\frac{\mathrm{E}[\widetilde{k}^*_{-j}]-\phi\theta}{2\phi(1-\phi)}\alpha_j-\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j\right)dA(\alpha_j)dB(\beta_j)dG(\varepsilon_j^0)dG(\varepsilon_j^1).
\end{aligned}
$$

Similarly, we can compute:

$$
\begin{aligned}
\Pi_j'(0)=&\min\{\theta,1-\theta,\phi,1-\phi\}C\\
&\times\iiint_{\underline{\alpha}\le F(\beta_j,\varepsilon_j^0,\varepsilon_j^1)\le\overline{\alpha}}\left(\frac{\mathrm{E}[\widetilde{k}^*_{-j}]-\phi\theta}{2\phi(1-\phi)}F(\beta_j,\varepsilon_j^0,\varepsilon_j^1)-\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\beta_j\right)\\
&\times A'(F(\beta_j,\varepsilon_j^0,\varepsilon_j^1))dB(\beta_j)dG(\varepsilon_j^0)dG(\varepsilon_j^1)\\
\ge&\min\{\theta,1-\theta,\phi,1-\phi\}C\left(\frac{\mathrm{E}[\widetilde{k}^*_{-j}]-\phi\theta}{2\phi(1-\phi)}\underline{\alpha}-\left(1-\frac{\mathrm{E}[\widetilde{k}^*_{-j}]}{2\phi}\right)\overline{\beta}\right)\\
&\times\iiint_{\underline{\alpha}\le F(\beta_j,\varepsilon_j^0,\varepsilon_j^1)\le\overline{\alpha}}A'(F(\beta_j,\varepsilon_j^0,\varepsilon_j^1))dB(\beta_j)dG(\varepsilon_j^0)dG(\varepsilon_j^1).
\end{aligned}
$$

The same argument as in Case (ii) shows that when $\overline{\varepsilon}$ is sufficiently large, $\lambda_j^*>0$.

(iii) $\mathrm{E}[\widetilde{k}^*_{-j}]=\phi\theta$. If $\lambda_j^*>0$, we have proved the proposition; otherwise, suppose $\lambda_j^*=0$. We have $p^j=\Pr(\hat{\beta}_j(\lambda_j^*)>0)=\Pr\left(\beta_j+\Delta\varepsilon_j>0\right)=1/2$. Correspondingly,

$$
\mathrm{E}[\widetilde{k}_j^*]=\frac{1}{2}\left(\min\{\theta,\phi\}+\max\{0,\theta+\phi-1\}\right)\neq\theta\phi.
$$

In fact, for $0 < \phi < 1/2$, $\mathrm{E}[\widetilde{k}_j^*] = \theta\phi$ if and only if $\theta = 0, 1/2, 1$, which we have excluded by assumption. Therefore, it must be that $\mathrm{E}[\widetilde{k}_j^*] < \theta\phi$ or $\mathrm{E}[\widetilde{k}_j^*] > \theta\phi$. In either case, we can repeat the proof above with j and $-j$ switched to conclude that $\lambda_{-j}^* > 0$. $\square$

In contrast to Proposition 1, Proposition 2 shows that competition drives at least one firm to choose positive penalization. In other words, competition favors a simpler algorithm design that reduces variance but at the cost of introducing bias. We provide below the economic intuition for this result.

Because the two consumer segments are of different sizes (by the assumption that $\phi \neq 1/2$), the one which is smaller will be ex-ante more competitive because when both firms target this segment, there will be higher expected overlap of the targeted consumers. Compared with the OLS estimator which induces a firm to concentrate targeting in one consumer segment (the one with higher estimated profitability), the penalization in the Lasso regression tends to induce the firm to target consumers across the two segments more evenly. When $\theta = 1/2$, the OLS and the Lasso will generate the same targeting outcome, because it amounts to the same 50% targeting probability on every consumer regardless of whether the firm targets the two consumer segments evenly or targets all the consumers evenly. Therefore, as long as $\theta \neq 1/2$, the penalization in the Lasso regression that induces more uniform targeting across consumers will reduce a firm's concentration of targeting on one particular consumer segment, which in turn reduces the expected overlap between the two firms' targeted consumers and thus softens competition. This can also be seen from equation (5), where a higher λ_j penalizes $\hat{\beta}_j(\lambda_j)$ towards zero and consequently, the competition avoidance incentive as captured by $(\phi\theta - \mathrm{E}[\widetilde{k}_{-j}^*])/(2\phi(1-\phi))$ has a relatively bigger impact on $\eta_j(\lambda_j)$ which determines firm j's targeting decision.

In fact, the competition avoidance incentive for firm j is present whenever $\mathrm{E}[\widetilde{k}_{-j}^*] \neq \phi\theta$—that is, when the competitor does not target all consumers equally. This provides firm j the strategic incentive to introduce bias to reduce the overlap in the targeting. In fact, as shown in the proof of Proposition 2 above, as long as $\mathrm{E}[\widetilde{k}_{-j}^*] \neq \phi\theta$, firm j will choose $\lambda_j^* > 0$ in equilibrium to lessen competition.

It is worthwhile to reiterate that in our modeling approach, different choices of λ_j by firm j determines different algorithm designs, which amounts to different ways to representing consumer information for decision making on targeting. Proposition 2 implies that competition favors a positive penalization that leads to more precise but less accurate information about consumer profitability. In fact, $\hat{\beta}_j(\lambda_j)$ will be non-zero only if the profit difference between two segments of consumers is big enough to compensate the profit loss from more intense competition resulting from more concentrated targeting. In other words, compared with the OLS estimator, the estimator of $\hat{\beta}_j(\lambda_j)$ will be not very accurate when $|\beta_j|$ is close to zero but more precise.

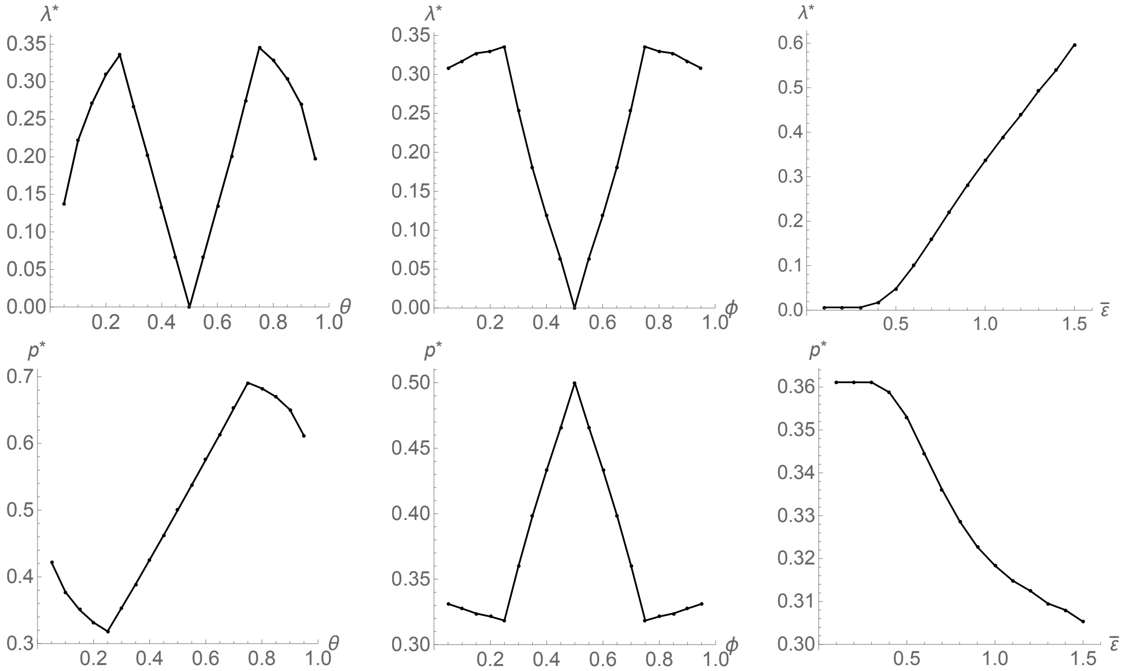
Lastly, we also require $\bar{\varepsilon}$ to be sufficiently high. With enough noise in the data, the risk of over-fitting becomes consequential. Moreover, a higher $\bar{\varepsilon}$ also implies a higher $\underline{\alpha}$ by Assumption 2, which translates into a higher incentive to avoid competition by equation (5). Both considerations make a positive penalization in the Lasso regression and the equilibrium choice of algorithmic bias more desirable.

5.4 Symmetric Equilibrium

Given our symmetric setup, it is natural to consider the symmetric equilibrium with $\lambda_1^* = \lambda_2^* = \lambda^*$. The corollary below is obvious from Proposition 2.

Corollary 1. *If a symmetric pure-strategy equilibrium exists, $\phi \neq 1/2$, $\theta \neq 1/2$ and $\bar{\varepsilon}$ is sufficiently high, then, we must have $\lambda^* > 0$.*

Figure 3 provides some some numeric examples of the equilibrium under uniform distributions and also examines the comparative statics. For all the parameter settings in Figure 3, we find that a pure-strategy symmetric equilibrium exists. There are several observations to make. First, notice that when $\theta < 1/2$ (as in the left half of panel (a) as well as the entire region of panels (b) and (c)), p^* decreases with λ^*. This is very intuitive—as the penalization gets higher, firms tend to target more evenly across the two consumer segments, which means reducing targeting probability in the more competitive segment—segment $x = 1$ in this case due to $\theta < 1/2$. On the other hand, when $\theta > 1/2$ (as in the right half of panel (a)), segment $x = 0$ is more competitive, so as λ^* increases, the firms allocate more targeting probability to the less competitive segment of $x = 1$, which means raising p^*. Second, we find that indeed for the two knife-edge cases of $\theta = 1/2$ and $\phi = 1/2$, $\lambda^* = 0$, as shown by panels (a) and (b); correspondingly, $p^* = 1/2$ in these cases. Thirdly, we find that the firms choose the maximum penalization when $\theta = \phi$ or $\theta = 1 - \phi$, as shown by panels (b) and (c). In fact, by calculation, one can show that these are the cases when the firms achieve the maximum reduction in consumer overlap by switching from targeting two segments evenly to targeting every consumer evenly. Therefore, these are the cases when the firms have the highest incentive to set a high penalization. Lastly, consistent with the standard statistic learning theory, as $\bar{\varepsilon}$ increases, the data gets noisier, and consequently, the firms choose a higher penalization to avoid the over-fitting problem, as shown by panel (c).



(a) $\phi = 0.25$ and $\bar{\varepsilon} = 1$ (b) $\theta = 0.25$ and $\bar{\varepsilon} = 1$ (c) $\phi = \theta = 0.25$

Figure 3: Equilibrium λ^* and p^* given $A \sim \text{Unif}[2, 4]$, $B \sim \text{Unif}[-1, 1]$, $G \sim \text{Unif}[-\bar{\varepsilon}, \bar{\varepsilon}]$.

6 Summary and Discussion

In this paper, we examine how competitive firms employ algorithms to estimate demand and based on the estimates, make strategic consumer targeting decisions to maximize expected profit. Algorithm design essentially implies different model selection strategies, which involve different bias and variance trade-offs under the general framework of supervised learning. This bias-variance trade-off also implies the extent of model flexibility that the firm would like to optimally use for targeting. From this perspective, our paper studies firms' competitive model selection for algorithmic targeting and explores how competition moderates individual firms' bias-variance trade-off choices through the degree of complexity of the algorithm that is adopted. The central finding is that targeting under competition favors simpler models that reduce variance but which introduce bias. There is therefore the suggestion that more flexible algorithms like deep learning are more likely to be valuable for firms with monopoly power.

We focus on a specific decision of the firms—targeting. Thanks to large advertising platforms such as Facebook or Google, there is an ongoing trend of advertising targeting decisions being automated by algorithms for real-time advertising deployment based on rich customer behavior data on browsing, purchase, sharing, observed social connections, etc. Targeting is therefore a natural context to study algorithmic competition and our model and payoff function is designed to represent the classic competitive targeting problem. Within this context, our result shows that competition favors algorithmic bias holds for quite general distributional assumptions about the prior beliefs. As next steps it would be interesting to explore a general class of oligopoly games with strategic firm decisions such as pricing, advertising or product design. The implications may depend on whether the firms' decisions are strategic substitutes or complements (Bulow et al. 1985).

Endogenous Data

We conclude by describing a setup which allows the targeting data-set to be generated from market competition. In the model of the paper we have assumed that each firm is endowed with an exogenous data-set. To allow for the data-sets to be endogenously generated from market interaction we will require the firms to compete in the targeting decisions at least twice, where the first-time competition generates the data, which is then utilized by the firms to devise their subsequent targeting strategies. Specifically, suppose that the game analyzed in the paper is modified through the following timeline. At time 0, the two firms simultaneously choose the tuning parameters. At time 1 where the first period begins, each firm decides on the consumers to target, who upon being targeted, decide whether to make a purchase. Each firm observes a noisy signal of the profit from each consumer who made a purchase. That is, we interpret $\pi_j(x)$ in the main model as firm j's average profit from an x-type consumer, and the firm's profit from an individual x-type consumer who made a purchase is $\pi_j(x)$ plus some idiosyncratic error (analogous to y_j^l in the main model). Based on the data, as before each firm delegates an analyst to estimate profit by running a Lasso regression. Based on the estimates, each firm devises the targeting strategy to maximize estimated profit in the second period.

In this modified game, each firm makes targeting decisions in the first period based on its prior belief. Given that β_j is distributed symmetrically around zero, it is optimal for each firm to target randomly. Notice that if a consumer is targeted by both firms, she makes a random choice between the two. This implies that observation of a targeted consumer's purchase decision does not give the firm any extra information for estimating the consumer profitability. Consequently, each firm first period actions result in a data-set of "$\pi_j(x_i)$ plus some idiosyncratic errors", where i is the consumer index that spans across all consumers who made a purchase from firm j in the first period. Even though this data-set is generated from the first period market interaction, it is qualitatively similar to that in the main model and could be equivalently seen as being generated from a monopoly market. Moreover, the firms' choice in tuning parameters at time 0 has no impact on their profits in the first period, so when choosing λ_j, each firm j faces the same decision problem as in the main model. To summarize, this extended two-period model that allows for the data-sets to be endogenous to the first period interaction is almost identical to our main model with exogenous data-sets, except that for each data-set, the number and types of consumers observed can be different. But this would not qualitatively alter the main result pertaining to the effect of competition on model selection.

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