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Flexible Multi-Index Binary Choice Models

Sriram Shankar*

Abstract

This paper develops a flexible class of binary choice models that relaxes the single-index restriction underlying standard logit and probit specifications. The proposed framework allows multiple component-specific indices to jointly determine the probability of success through a multiplicative structure, accommodating both probit and logit link functions while retaining analytical tractability. We characterise marginal effects and relative marginal effects within this framework and show that, unlike standard single-index models where relative marginal effects are fixed by parameter ratios, the proposed specification allows them to vary with the covariates. This structure gives rise to flexible marginal responses and endogenous interaction effects without requiring explicit interaction terms. The model also admits a useful logarithmic representation that connects it to a structured and interpretable approximation of unknown choice probability functions, analogous to a restricted neural network. Despite its added flexibility, the model can be estimated using standard maximum likelihood methods. Overall, the framework provides a tractable and interpretable extension of conventional binary choice models that captures more complex behavioural responses while preserving the empirical appeal of logit and probit approaches.

Keywords: Binary choice models; Logit model; Probit model; Multi-index models; Marginal effects; Interaction effects; Neural network approximation

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1 Introduction

Standard binary choice models such as the logit and probit remain the workhorses of applied econometric analysis due to their tractability, clear interpretation, and strong microfoundations (McFadden, 1974; Amemiya, 1981; Train, 2009). Their widespread use spans a broad range of applications, including labour supply, health, environmental choice, and industrial organisation (Cameron and Trivedi, 2005; Wooldridge, 2010). Despite these advantages, the canonical formulations rely on a single-index structure that imposes important restrictions on the way explanatory variables shape choice probabilities.

In particular, standard models assume that explanatory variables enter the decision problem through a linear index, with choice probabilities given by $P(y = 1 \mid x) = F(x'\beta)$. This representation implies that all covariates affect outcomes through a common scalar index, thereby constraining the flexibility of marginal effects. Relative marginal effects in these models are largely governed by fixed parameter ratios, which limits the flexibility of how covariates influence outcomes. As a result, standard single-index models may be unable to adequately capture settings in which multiple underlying mechanisms jointly determine outcomes, particularly when these mechanisms interact in nonlinear or multiplicative ways.

A related limitation concerns the treatment of interaction effects. In standard specifications, cross-variable interactions must be introduced explicitly through additional terms in the index. While this approach can accommodate simple forms of dependence, it quickly becomes cumbersome as the number of covariates increases and may fail to capture richer patterns of interaction among explanatory variables. Moreover, such interactions are imposed *ex ante* and remain tied to the single-index structure, rather than arising endogenously from the model.

This paper considers a class of binary choice models that address these limitations by relaxing the single-index assumption. Specifically, we develop a framework in which multiple latent indices contribute jointly to the determination of choice probabilities through a multiplicative structure. Under this formulation, distinct components represent differ-

ent underlying mechanisms, and their interaction emerges naturally through the aggregation of probabilities. This generates endogenous interaction effects and covariate-dependent marginal responses without the need for ad hoc interaction terms in the index.

The proposed approach provides a more flexible representation of decision processes in which outcomes depend on the joint realization of several factors. At the same time, the framework remains analytically tractable and can be estimated using standard likelihood-based methods. Importantly, it yields richer comparative statics by allowing relative marginal effects and interaction patterns to vary flexibly across the covariate space, beyond the restrictions imposed by standard single-index models.

The remainder of the paper is organised as follows. Section 2 examines the limitations of standard logit and probit models. Section 3 discusses functional-form extensions within the single-index framework that, to some extent, address these limitations. Section 4 presents the proposed multi-index multiplicative framework, characterises its main properties and outlines estimation. Section 5 concludes.

2 Limitations of Standard Logit and Probit Models

Standard binary choice models are typically specified as

$$P(y = 1 \mid x) = F(x'\beta), \tag{1}$$

where $F(\cdot)$ denotes a cumulative distribution function such as the normal cumulative distribution function in the probit model or the logistic cumulative distribution function in the logit model, and $x'\beta$ is a linear index. These models remain widely used because of their tractability, clear interpretation, and well-established econometric properties. Nevertheless, the underlying single-index structure imposes several restrictive features that may limit their flexibility in empirical applications.

A central restriction is that all covariates affect the outcome only through the scalar

index $z = x'\beta$. Consequently, marginal effects take the form

$$\frac{\partial P}{\partial x_k} = f(z)\beta_k, \tag{2}$$

where $f(z) = F'(z)$. Since all covariates share the same multiplicative term $f(z)$, the ratio of marginal effects across covariates is given by

$$\frac{\partial P/\partial x_i}{\partial P/\partial x_j} = \frac{\beta_i}{\beta_j}. \tag{3}$$

Thus, relative marginal effects are determined solely by parameter ratios and are invariant to the state of the system as characterised by the explanatory variables. While the overall magnitude of marginal effects varies with the value of the index, the relative marginal effect of one covariate with respect to another remains fixed across observations. Consequently, a change in the values of the explanatory variables cannot alter the effect of one covariate relative to another.

The single-index structure also imposes a restrictive form of interaction across covariates. Cross-partial effects are given by

$$\frac{\partial^2 P}{\partial x_i \partial x_j} = f'(z)\beta_i\beta_j, \tag{4}$$

which depend only on the curvature of the link function and the product of coefficients. These cross-partial derivatives measure how the marginal effect of one explanatory variable changes as another explanatory variable changes, and therefore capture interaction effects between covariates. In standard logit and probit models, such interaction effects are driven entirely by movements in the common index $z = x'\beta$. As a result, the way in which one covariate modifies the effect of another is tightly constrained by the functional form of the link function and cannot vary flexibly across variables or observations. More complex interaction patterns therefore do not arise naturally from the structure of the model and must instead

be introduced explicitly through additional interaction terms in the index specification.

The shape of marginal effects is also tightly constrained in standard single-index models. Since

$$\frac{\partial P}{\partial x_k} = f(z)\beta_k,$$

where $z = x'\beta$ and $f(z)$ is the derivative of the link function, all covariates share the same underlying response pattern determined by the common function $f(z)$. The coefficients β_k affect only the magnitude and direction of the response. As a result, the effect of different covariates on the outcome probability cannot evolve independently as covariates change.

To illustrate, consider a standard logit model for the probability that a household adopts a new agricultural technology, where $y = 1$ denotes adoption of the technology and $y = 0$ otherwise. Suppose the explanatory variables include household income and years of education:

$$P(y = 1 \mid x) = \Lambda(z),$$

with

$$z = -4 + 0.08\,\text{Income} + 0.5\,\text{Education},$$

and

$$\Lambda(z) = \frac{e^z}{1 + e^z}.$$

The marginal effects are

$$\frac{\partial P}{\partial \text{Income}} = \Lambda(z)(1 - \Lambda(z)) \times 0.08,$$

and

$$\frac{\partial P}{\partial \text{Education}} = \Lambda(z)(1 - \Lambda(z)) \times 0.5.$$

Both marginal effects are therefore governed by the same function $\Lambda(z)(1 - \Lambda(z))$.

Suppose education is fixed at 4 years. Table 1 shows how the probability of adoption and the marginal effects change as income increases.

Table 1: Marginal effects in a standard logit model

Income	$P(y = 1)$	$\frac{\partial P}{\partial \text{Income}}$	$\frac{\partial P}{\partial \text{Education}}$
10	0.2315	0.0142	0.0889
30	0.5987	0.0192	0.1201
50	0.8808	0.0084	0.0525
70	0.9734	0.0021	0.0130
90	0.9945	0.0004	0.0027

The marginal effect of income initially rises and then declines as the probability of adoption approaches one. However, the marginal effect of education must follow exactly the same qualitative pattern because both effects are proportional to the same function of the common index. The only difference is scale, determined by the coefficients 0.08 and 0.5.

Consequently, the model cannot generate fundamentally different nonlinear response patterns in the outcome probability across covariates. For example, it cannot easily accommodate situations in which the effect of income diminishes at higher income levels while the effect of education remains stable or becomes stronger. More generally, the single-index structure imposes a common response-shape restriction on the effects of all covariates.

In addition, the sign of the marginal effect is determined entirely by the sign of β_k, since $f(z) > 0$. Consequently, the probability of success is monotonic in each explanatory variable, holding other covariates fixed. A covariate can therefore only have either a uniformly increasing or uniformly decreasing effect on the outcome probability. Furthermore, the model cannot naturally capture situations in which the effect of a variable changes direction as other covariates vary, unless nonlinear transformations or additional interaction terms are introduced explicitly into the specification.

Taken together, these features suggest that standard logit and probit models, despite their simplicity and empirical usefulness, may not be sufficiently flexible in settings where outcomes are influenced by multiple interacting factors, where the relative importance of explanatory variables (relative marginal effects) changes with the values of the covariates, or where covariates exhibit different nonlinear response patterns. These limitations motivate functional form extensions within the single-index framework that preserve the single-index structure while introducing nonlinear responses, richer interactions, and more flexible marginal effects.

3 Functional Form Extensions within the Single-Index Framework

A common approach to relaxing the limitations of standard logit and probit models is to replace the linear index with a more flexible function of the covariates. Consider the general specification

$$P(y = 1 \mid x) = F\big(g(x)\big), \tag{5}$$

where $F(\cdot)$ is a monotonic link function and $g(x)$ is a nonlinear function of the explanatory variables. Letting $z = g(x)$, marginal effects are given by

$$\frac{\partial P}{\partial x_k} = f(z)\frac{\partial g(x)}{\partial x_k}, \tag{6}$$

where $f(z) = F'(z)$. The flexibility of the model therefore depends on the functional form chosen for $g(x)$. In practice, a common strategy is to augment the standard single-index specification using quadratic terms, interaction terms, or combinations of both. These specifications can partially relax some of the restrictions of the standard logit and probit models by allowing relative marginal effects, interaction patterns, and monotonicity properties to vary with the covariates.

Consider first a quadratic specification of the form

$$g(x) = \sum_k \beta_k x_k + \sum_k \gamma_k x_k^2. \tag{7}$$

The marginal effect of covariate x_k is then

$$\frac{\partial P}{\partial x_k} = f(z)\big(\beta_k + 2\gamma_k x_k\big), \tag{8}$$

so that relative marginal effects are given by

$$\frac{\partial P/\partial x_i}{\partial P/\partial x_j} = \frac{\beta_i + 2\gamma_i x_i}{\beta_j + 2\gamma_j x_j}. \tag{9}$$

Unlike the standard single-index model, relative marginal effects now vary with the levels of the covariates. The specification also allows for nonlinear responses and turning points, including U-shaped or inverted U-shaped relationships. In addition, the sign of the marginal effect may vary with the value of the covariate. As shown in equation (8), monotonicity with respect to x_k depends on the sign of $(\beta_k + 2\gamma_k x_k)$, which may change as the covariate varies. Consequently, the relationship need not be monotonic. However, the model does not introduce interaction across variables, since each covariate affects the outcome independently through its own nonlinear transformation. Moreover, the resulting nonlinearities remain restricted to a quadratic parametric form.

A second approach introduces interaction effects directly through cross-product terms:

$$g(x) = \sum_k \beta_k x_k + \sum_{i \neq j} \gamma_{ij} x_i x_j. \tag{10}$$

Marginal effects become

$$\frac{\partial P}{\partial x_k} = f(z)\left(\beta_k + \sum_{j \neq k} \gamma_{kj} x_j\right), \tag{11}$$

implying

$$\frac{\partial P/\partial x_i}{\partial P/\partial x_j} = \frac{\beta_i + \sum_{k \neq i} \gamma_{ik} x_k}{\beta_j + \sum_{k \neq j} \gamma_{jk} x_k}. \tag{12}$$

Relative marginal effects therefore depend on the values of other explanatory variables. This specification also allows the marginal effect of one covariate to vary with the level of another covariate, thereby introducing interaction effects directly into the model. The sign of the marginal effect can now depend on the broader configuration of covariates.

As a result, the effect of a given covariate need not remain monotonic across different values of the other covariates. Nevertheless, while the interaction specification captures cross-variable dependence, it does not introduce additional covariate-specific nonlinearities beyond those implied by the nonlinear link function. [1] More importantly, interaction patterns remain entirely determined by the imposed parametric structure.

A more flexible specification augments the linear index with both quadratic and interaction terms:

$$g(x) = \sum_k \beta_k x_k + \sum_k \gamma_k x_k^2 + \sum_{i \neq j} \delta_{ij} x_i x_j. \tag{13}$$

Marginal effects are then given by

$$\frac{\partial P}{\partial x_k} = f(z) \left(\beta_k + 2\gamma_k x_k + \sum_{j \neq k} \delta_{kj} x_j \right), \tag{14}$$

so that the magnitude and sign of the marginal effect depend both on the level of x_k itself and on the levels of other covariates through the interaction terms. Relative marginal effects are therefore no longer determined solely by fixed parameter ratios. Instead, relative marginal effects become covariate dependent because the partial derivatives of the index function

[1] For example, consider an index of the form $z = \beta_1 x_1 + \beta_2 x_2 + \delta x_1 x_2$. The marginal effect of x_1 is given by $\partial z/\partial x_1 = \beta_1 + \delta x_2$, implying that the effect of x_1 varies with the level of x_2. Although the nonlinear link function in logit and probit models generates curvature in the outcome probability through its dependence on z, this curvature is common to all covariates and is inherited from the single-index structure. The interaction term itself does not create independent nonlinear curvature with respect to x_1, since $\partial^2 z/\partial x_1^2 = 0$. Capturing richer covariate-specific nonlinear responses, such as diminishing or increasing marginal effects in x_1, requires additional nonlinear transformations, such as x_1^2, to be introduced explicitly.

depend on the covariates through the quadratic and interaction terms in equation (13). This specification provides the greatest flexibility among the three alternatives considered here, since it allows for curvature, interaction effects, and relationships that need not remain monotonic as covariate values change. In particular,

$$\frac{\partial g(x)}{\partial x_k} = \beta_k + 2\gamma_k x_k + \sum_{j \neq k} \delta_{kj} x_j, \tag{15}$$

implying that the sign and magnitude of marginal effects may vary across observations depending on the configuration of explanatory variables. However, despite this increased flexibility, the model remains fundamentally constrained by the chosen polynomial structure. The shape of responses, turning points, and interaction patterns are all imposed parametrically rather than arising endogenously from the model structure.

Across all three specifications, the probability of success continues to take the form

$$P(y = 1 \mid x) = F\big(g(x)\big), \tag{16}$$

so that outcomes are still determined through a single scalar index. Although nonlinear and interaction terms substantially improve flexibility relative to the standard linear-index formulation, they do not fundamentally relax the single-index restriction. In particular, all marginal effects continue to be scaled by the common function $f(z)$, interaction structures must be specified explicitly, and nonlinearities remain tied to the chosen functional form of $g(x)$. These considerations suggest that a more fundamental departure from the single-index framework may be required to capture richer forms of interaction and more flexible covariate-dependent marginal effects, motivating the alternative approach developed in the next section.

4 A Multiplicative Multi-Index Binary Choice Model

This section introduces a flexible class of binary choice models that relax the single-index restriction underlying standard logit and probit specifications. The key idea is to allow multiple latent components to jointly determine the probability of success through a multiplicative structure. Rather than relying on a single scalar index, the proposed framework permits several latent mechanisms to contribute simultaneously to the observed outcome. This provides a more flexible representation of binary choice behaviour while retaining analytical tractability and a familiar probabilistic structure.

4.1 Model Specification

Let $j = 1, \ldots, J$ index distinct latent components. For each component, define the latent index

$$z_j = x'\beta_j, \tag{17}$$

where β_j is a component-specific parameter vector. Let $F(\cdot)$ denote a cumulative distribution function, which may take either the normal cumulative distribution function in the probit case or the logistic cumulative distribution function in the logit case. The probability of success is specified as

$$P(y = 1 \mid x) = \prod_{j=1}^{J} \big[F(z_j)\big]^{\xi_j}, \tag{18}$$

where $\xi_j > 0$ are weights governing the contribution of each component.

The model therefore generalises the standard single-index specification by allowing multiple linear indices to jointly enter the choice probability through a multiplicative aggregation of transformed probabilities. Intuitively, each component may be interpreted as representing a distinct latent mechanism or channel influencing the probability of success. The multiplicative form implies that the final probability depends on the joint contribution of these underlying components.

For analytical purposes, it is useful to consider the logarithmic representation

$$\log P = \sum_{j=1}^{J} \xi_j \log F(z_j). \tag{19}$$

This transformation does not alter the underlying multiplicative structure but provides a convenient representation for deriving marginal effects.

The formulation also admits an interpretation related to artificial neural network representations. Each term $F(x'\beta_j)$ corresponds to a nonlinear transformation of a linear index, while $\log F(x'\beta_j)$ may be interpreted as a transformed activation function. The log-probability therefore takes the form of a weighted combination of nonlinear activations, analogous to a restricted [2] single-hidden-layer neural network. Standard approximation results for neural networks (Hornik et al., 1989) imply that sufficiently rich combinations of nonlinear components can approximate a broad class of functions. The present specification may therefore be viewed as a structured and interpretable approximation framework embedded within a probabilistic binary choice model. Unlike fully nonparametric neural network approaches, however, the model retains a clear econometric structure and interpretable component-specific parameters.

Marginal effects are given by

$$\frac{\partial P}{\partial x_k} = P \sum_{j=1}^{J} \xi_j \frac{f(z_j)}{F(z_j)} \beta_{jk}, \tag{20}$$

where $f(z_j) = F'(z_j)$. Relative marginal effects take the form

$$\frac{\partial P/\partial x_i}{\partial P/\partial x_k} = \frac{\sum_{j=1}^{J} \xi_j \frac{f(z_j)}{F(z_j)} \beta_{ji}}{\sum_{j=1}^{J} \xi_j \frac{f(z_j)}{F(z_j)} \beta_{jk}}. \tag{21}$$

[2] The representation resembles a restricted single-hidden-layer neural network in which the component-specific indices $x'\beta_j$ are transformed through nonlinear activation functions and combined linearly in log-probability space. Unlike a general neural network, however, the specification is constrained by the probabilistic structure of the model, including the requirement that $\xi_j > 0$ to ensure well-defined probabilities.

Unlike standard logit and probit models, relative marginal effects are no longer determined solely by parameter ratios. Instead, they depend on multiple nonlinear component-specific terms evaluated at different indices, so that the ratio of marginal effects becomes a function of the covariates through the induced variation in z_j.

The model also generates endogenous interaction effects. Differentiating again yields

$$\frac{\partial^2 \log P}{\partial x_i \partial x_k} = \sum_{j=1}^{J} \xi_j \left[\frac{f'(z_j)F(z_j) - f(z_j)^2}{F(z_j)^2} \right] \beta_{ji}\beta_{jk}. \tag{22}$$

These cross-partial effects arise naturally from the multiplicative multi-index structure and do not require interaction terms to be imposed explicitly in the specification. Consequently, the effect of one covariate may vary flexibly with the levels of other covariates through the interaction of component-specific nonlinearities.

The model further allows more flexible marginal effect patterns than standard single-index specifications. Holding other covariates fixed, marginal effects are weighted combinations of nonlinear functions evaluated at multiple indices, so that each explanatory variable can display distinct nonlinear responses through its heterogeneous effects on the component-specific indices. In computing the marginal effect with respect to x_k, all other covariates are held fixed. In this case,

$$\text{sign}\left(\frac{\partial P}{\partial x_k}\right) = \text{sign}\left(\sum_{j=1}^{J} \xi_j \frac{f(z_j)}{F(z_j)} \beta_{jk}\right), \tag{23}$$

so that the sign of the marginal effect is not determined solely by β_{jk}, but by a weighted sum of component-specific contributions. The weights $\frac{f(z_j)}{F(z_j)}$ vary with x_k through the indices $z_j = x'\beta_j$. As a result, monotonicity with respect to x_k is not guaranteed: the marginal effect may vary in magnitude and may potentially change sign as x_k changes, even when other covariates are held fixed.

4.2 Estimation

Despite its greater flexibility, the proposed framework retains many of the attractive features of standard logit and probit models. Letting

$$P_i = \prod_{j=1}^{J} \left[F(x_i'\beta_j)\right]^{\xi_j}, \tag{24}$$

the likelihood contribution for observation i is

$$P_i^{y_i}(1-P_i)^{1-y_i}, \tag{25}$$

and the corresponding log-likelihood function is

$$\mathcal{L}(\{\beta_j\},\{\xi_j\}) = \sum_{i=1}^{N} \left[y_i \log P_i + (1-y_i)\log(1-P_i)\right]. \tag{26}$$

The likelihood function[3] can be evaluated directly and estimated using standard maximum likelihood techniques. Estimation therefore proceeds in a manner similar to conventional logit and probit models, relying on standard likelihood-based numerical optimisation methods together with familiar procedures for statistical inference and standard error estimation.[4]

[3]Identification requires that the component-specific indices $z_j = x'\beta_j$ generate sufficiently distinct variation over the support of the covariates. In particular, if $\beta_j = \beta_k$ for some $j \neq k$, then

$$[F(z_j)]^{\xi_j}[F(z_k)]^{\xi_k} = [F(z_j)]^{\xi_j+\xi_k},$$

so that only the combined weight $\xi_j + \xi_k$ is identified. More generally, weak identification may arise when the indices $x'\beta_j$ are highly collinear or exhibit limited independent variation in the sample. Since the ordering of latent components is observationally irrelevant, different parameterizations may generate identical choice probabilities. Additional restrictions may therefore be imposed to eliminate such observational equivalence, for example through ordering conditions such as $\xi_1 \geq \xi_2 \geq \cdots \geq \xi_J$, or by normalizing the component weights through $\sum_{j=1}^{J} \xi_j = 1$.

[4]Inference can be conducted using the inverse Hessian matrix evaluated at the maximum likelihood estimates or, where appropriate, heteroskedasticity-robust covariance estimators.

5 Conclusion

This paper has developed a multiplicative multi-index framework for binary choice analysis that relaxes the restrictive single-index structure underlying standard logit and probit models. The proposed specification allows multiple latent components to jointly determine the probability of success through a multiplicative aggregation mechanism, thereby providing a more flexible representation of binary outcomes.

The analysis has shown that the framework generates several important departures from conventional single-index models. In particular, relative marginal effects are no longer determined solely by fixed parameter ratios. Instead, they vary with the covariates through the component-specific indices, allowing the relative effects of explanatory variables on the outcome probability to differ across observations. The model also generates endogenous interaction effects through the multiplicative structure itself, rather than requiring interaction terms to be imposed explicitly in the index specification. In addition, the framework permits richer nonlinear response patterns and more flexible monotonicity properties than those available under standard logit and probit formulations.

The connection between the proposed specification and neural network representations further highlights the flexibility of the model. By combining multiple nonlinear transformations of latent indices, the framework can approximate a broad range of functional relationships while retaining a transparent probability-based interpretation and a tractable econometric structure. At the same time, despite its additional flexibility, estimation can still be conducted using familiar maximum likelihood techniques. More broadly, the framework provides a flexible alternative to standard single-index models by accommodating richer interaction effects, nonlinear response patterns, and covariate-dependent marginal effects while largely preserving the simplicity and practical appeal of conventional binary choice models. Future research may consider extensions to panel data settings, semiparametric specifications, and alternative forms of nonlinear aggregation.

CRediT authorship contribution statement

Sriram Shankar: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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