The Time-Varying Effects of Racial Representations in TV Commercials on Brand Health Metrics

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Abstract

This study examines the time-varying effects of Black actor representation in TV advertising on brand health metrics using a Time-Varying Parameter Vector Autoregressive model. Analyzing data from around 400 brands in 10 industries spanning 104 weeks around George Floyd's death, we investigate how Black actor share of ads (BASOA) impacts awareness and purchase intention of a brand. While increased BASOA generates positive awareness, it does not significantly affect purchase intention overall. BASOA effects tend to peak around race-related events, and impulse response analysis demonstrates positive transient and persistent effects on awareness, but negative immediate and positive longer-term effects on purchase intention. Our findings provide novel insights into the dynamic relationship between racial representation and brand performance, highlighting the importance of considering temporal context and brand heterogeneity when implementing these initiatives.

Keywords: Racial representation, Time-varying effects, Brand health metrics.

Track: Advertising & Marketing Communications.

1. Introduction

The topic of Diversity, Equity, and Inclusion (DEI) has gained significant attention across various domains (Bernstein et al., 2020; Ferraro et al., 2023; Hartmann et al., 2023). These initiatives are driven by consumers' expectations for authentic DEI efforts and brands' desire to demonstrate their social responsibility (Akestam et al., 2017; Schau et al., 2009; Wang et al., 2022). However, the impact of DEI initiatives on brands is complex, with effectiveness varying significantly across brands. For instance, McDonald's perceived performative support for Black Lives Matter backfired as their policies failed to adequately protect Black employees during the Covid-19 pandemic (Regalado, 2020). In contrast, Nike's Dream Crazy Campaign, featuring Colin Kaepernick, advocated against racial injustice and achieved significant success (Rucker, 2018).

In this research, we examine the impact of racial minority representation in TV advertisements on two brand health metrics: ad awareness and purchase intention, which represent different stages of consumer decision-making. TV advertising as an conventional tool remains a powerful for conveying messages to consumers (Pauwels et al., 2016).

Given the ever-evolving marketing environment, the effects of marketing efforts, such as racial representation in ads, may vary significantly over time. As such initiatives remain a relatively new territory, a mutual learning process unfolds: brands experiment with strategies while consumers update their perceptions. This dynamic interplay echoes broader insights from marketing research. For instance, Osinga et al. (2010) demonstrate that both persistent and transient marketing effects are strongest immediately after a brand's introduction and diminish over time. In contexts like racial representation, social dynamics play a crucial role. Events like George Floyd's death act as external shocks that may amplify consumer sensitivity and accelerate brand-consumer interactions. Therefore, evaluating the effectiveness of minority representation without incorporating time-specific insights might be suboptimal (Saboo et al., 2016).

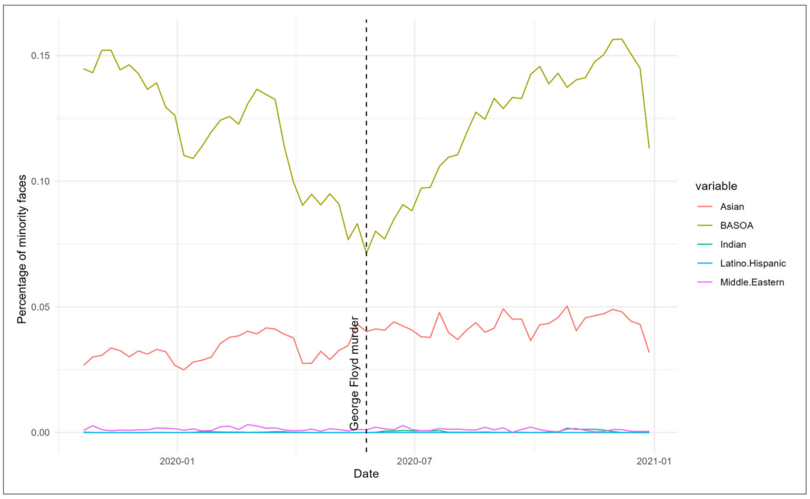
Our research contributes to existing literature in three ways. First, we address the empirical evidence gap using longitudinal data from TV ads and consumer responses. Second, apart from Hartmann et al. (2023), which examines immediate effects of featuring Black models in display advertisements around George Floyd's death, no research has investigated time-varying effects of racial representation in advertising. We address this using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to capture the evolving relationship between minority representation and advertising effectiveness. Third, we quantify the transient and persistent effects of minority representation efforts.

2. Data

The dataset combines two sources: advertisement-related variables and consumers' brand perceptions. Advertisement data comes from iSpot, a platform measuring TV advertisement performance using 52 million smart TVs and set-top boxes in the U.S., covering 666 brands from January 2018 to July 2021 (Overgoor et al., 2023).

The key measure, the Black actor share of advertisements (BASOA), represents the percentage of Black actors in a brand's daily airings. Figure 1, consistent with Hartmann et al. (2023), shows greater variance in Black actor representation compared to other minority groups. After George Floyd's death, BASOA increased for six months before declining, while other minority representation remained stable. BASOA was measured using YOLOv5Face (Qi et al., 2022) for face detection and LightFace (Serengil & Ozpinar, 2021) for race classification. The advertisement dataset also includes variables such as gender representation (i.e., percentage of female faces), total number of detected faces in ads, and total advertisement airings.

Figure 1: Evolution of minority representation in TV advertisements



The second dataset, from YouGov BrandIndex, tracks daily brand perception metrics through consumer panels (Garside, 2023; Overgoor et al., 2023; Rust et al., 2021). Data were merged and aggregated weekly, analysing 52 weeks before and after 25 May 2020.

3. Model

3.1. Model specification

We first assess the stationarity of each series through unit root tests, finding no stochastic trends. We expect dynamic two-way dependence between BASOA and brand health metrics.[1] To address this dependence and avoid spurious relationships, we employ multi-equation time series models with time-varying coefficients,[2] and propose the following TVP-VAR model:

$$Y_t = \alpha_t + \Phi_{1,t}Y_{t-1} + \cdots + \Phi_{p,t}Y_{t-p} + \Gamma_{1,t}X_{t-1} + \cdots + \Gamma_{p,t}X_{t-p} + \varepsilon_t \tag{1}$$

This can also be written as:

$$\begin{bmatrix} \mathrm{BHM}_t \\ \mathrm{BASOA}_t \end{bmatrix} = \begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \end{bmatrix} + \begin{bmatrix} \phi_{11t}^{(1)} & \phi_{12t}^{(1)} \\ \phi_{21t}^{(1)} & \phi_{22t}^{(1)} \end{bmatrix} \begin{bmatrix} \mathrm{BHM}_{t-1} \\ \mathrm{BASOA}_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \phi_{11t}^{(p)} & \phi_{12t}^{(p)} \\ \phi_{21t}^{(p)} & \phi_{22t}^{(p)} \end{bmatrix} \begin{bmatrix} \mathrm{BHM}_{t-p} \\ \mathrm{BASOA}_{t-p} \end{bmatrix}$$
$$+ \begin{bmatrix} \gamma_{11t}^{(1)} & \gamma_{12t}^{(1)} & \gamma_{13t}^{(1)} \\ \gamma_{21t}^{(1)} & \gamma_{22t}^{(1)} & \gamma_{23t}^{(1)} \end{bmatrix} \begin{bmatrix} \mathrm{Num\_Faces}_{t-1} \\ \mathrm{Female\_Ratio}_{t-1} \\ \mathrm{Num\_Airings}_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \gamma_{11t}^{(p)} & \gamma_{12t}^{(p)} & \gamma_{13t}^{(p)} \\ \gamma_{21t}^{(p)} & \gamma_{22t}^{(p)} & \gamma_{23t}^{(p)} \end{bmatrix} \begin{bmatrix} \mathrm{Num\_Faces}_{t-p} \\ \mathrm{Female\_Ratio}_{t-p} \\ \mathrm{Num\_Airings}_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{2}$$

where BHM_t denotes the brand health metric at time t. BASOA, Num_faces, Female_ratio, and Num_airings represent Black actors' share of advertisements, number of faces, percentage of female faces, and number of airings. The subscript t-k indicates lagged variables. We refer to $\sum_{k=1}^{p} \phi_{12t}^{(k)}$ as the BASOA effect. All variables are log-transformed. Particularly for BASOA, we first add 1 to the percentage value (pre-multiplied by 100). Lag length p is chosen with Bayesian Information Criterion and autocorrelation checks.

3.2. Model estimation

We estimate the TVP-VAR model using R's tvReg package (Casas & Fernández-Casal, 2022), employing kernel smoothing estimation that accommodates various error distributions. The tvVAR function assumes no serial correlation but relaxes homoskedasticity and normality assumptions.

[1]For a similar discussion on model identification, see Shapiro et al. (2021)

[2]While we explore BASOA's impact on brand health metrics, we do not claim causality due to: (i) non-random advertising assignment and (ii) unobserved confounders. Future research will consider matching, synthetic controls, or randomised experiments (Yılmaz et al., 2022).

We then compute impulse response functions (IRFs) to measure BASOA shock impacts over a 26-week horizon, determining transient versus persistent effects. Orthogonal IRFs are obtained through Cholesky decomposition of the time-varying covariance matrix (Casas & Fernández-Casal, 2022; Chang & Sakata, 2007).

4. Results

4.1. Main model estimation results

After removing outliers, the final sample includes approximately 400 brands with valid results. Over half the brands exhibit positive average BASOA coefficients in the ad awareness model, while purchase intention shows the reverse. The overall mean and median BASOA coefficients are 0.0034 and 0.0015 for ad awareness, and 0.0003 and 0.0000 for purchase intention. Statistically, 11.47% and 13.53% of brand-level estimates in the two models are indistinguishable from zero. Median pre-/post-GF values are 0.0033 vs. 0.0017 for ad awareness, and 0.0005 vs. 0.0000 for purchase intention. On average, lagged BASOA efforts are positively linked to ad awareness but unrelated with purchase intention, with lower effects observed post-GF.

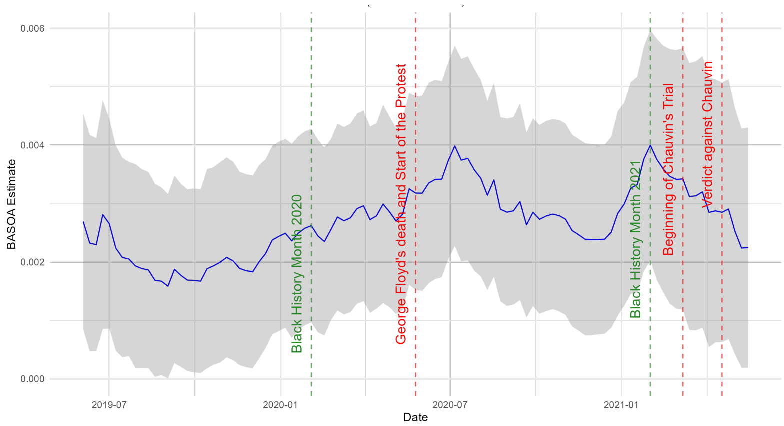
Figure 2 shows the evolution of brand-level average BASOA coefficients estimates over time. For ad awareness, BASOA coefficients peak locally at race-related events, rising before GF, peaking a month after, then declining. The trend resurges during Black History Month 2021 before subsiding. For purchase intention, coefficients generally decline, with a brief uptick following GF.

4.2. Brand-level BASOA effect changes

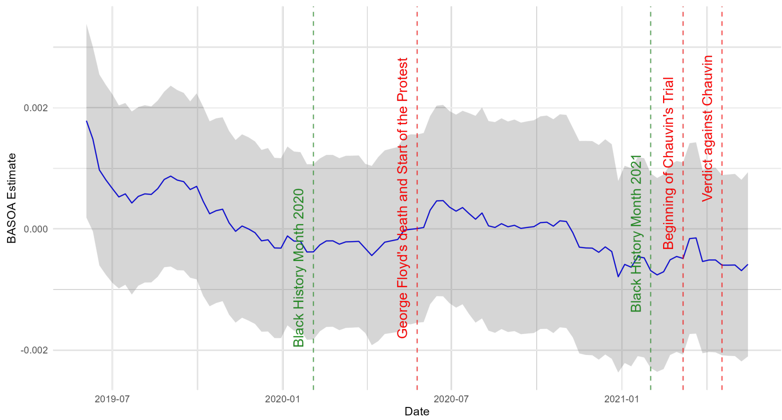
Having established the time-varying nature of BASOA effects, we examined how the effect changes at brand-level. We computed the average BASOA coefficient estimates before-/after-GF for each brand, finding that most brands maintain consistent sign direction. For ad awareness, only 28 and 34 brands out of 420 brands with valid results show a sign change from positive to negative and negative to positive, respectively. The corresponding figures for purchase intention are 30 and 16 brands out of 432 brands.

Figure 3 shows the plot for brands with strict sign changes in the Restaurant industry. The y-axis displays the log-transformed BASOA level, revealing relative changes in

Figure 2: Evolution of BASOA effects



(a) Ad Awareness



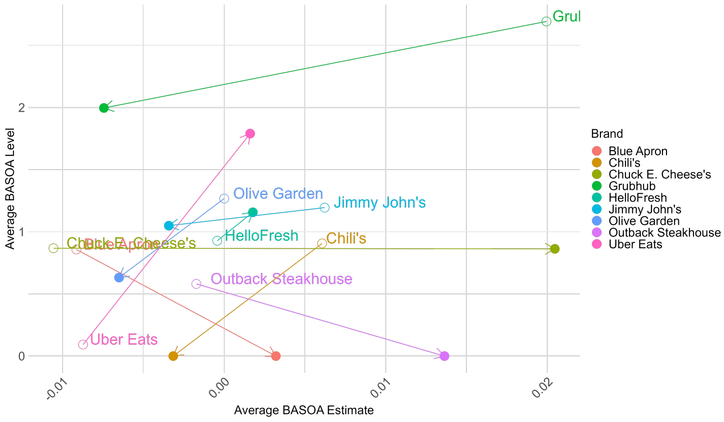
(b) Purchase Intention

BASOA level and effects. For example, in the purchase intention model, Domino's shifted from a lower BASOA level with positive coefficient before GF to a higher BASOA level with negative coefficient after GF, while Grubhub shows an opposite pattern. This suggests that a brand's purchase intention may benefit or suffer as it increases BASOA.

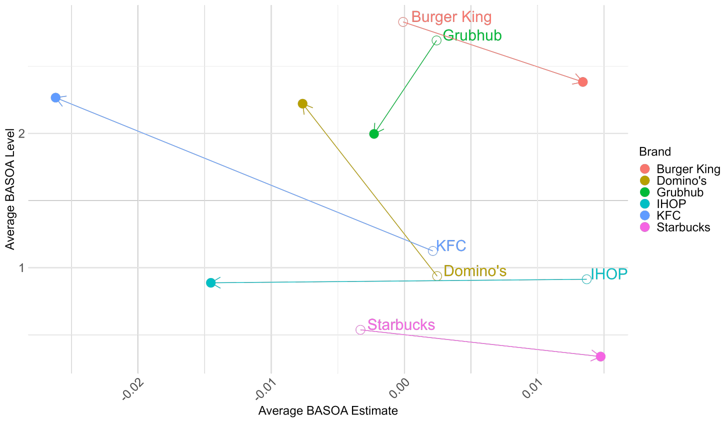
4.3. IRF analysis

Many companies often synchronise their actions of increasing minority representation with race-related events when public interest peaks. To examine the impact of such BASOA efforts, we use impulse response functions (IRF). BASOA is specified as the impulse and brand health metrics as the response, focusing on how a BASOA shock propagates and affects outcomes. Shocks are assumed to be orthogonal, meaning only BASOA is externally increased at specified time points. We analyze four minority-related events: 1 recurring event, Black History Month February 2021, and 3 one-time events:

Figure 3: Brands with Sign Changes in BASOA Effects Before vs. After GF



(a) Ad Awareness



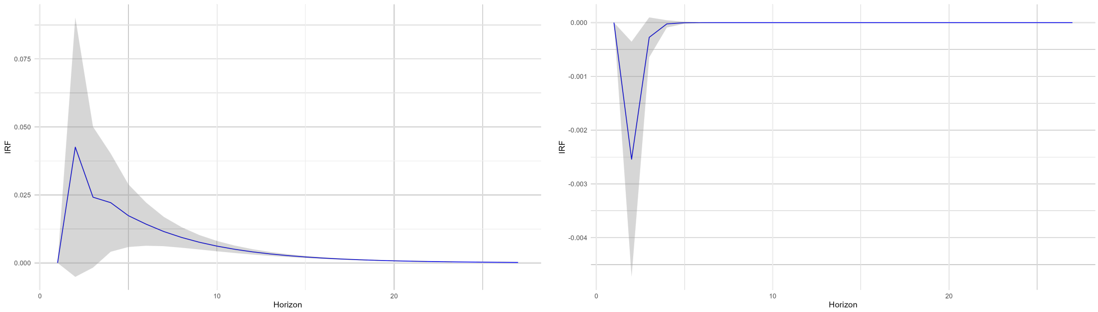
(b) Purchase Intention

George Floyd's death and the start of protests, the beginning of Chauvin's trial, and the verdict against Chauvin (Hartmann et al., 2023). Effects are evaluated over four horizons: immediate effect (within 1 week), short-term effect (within 4 weeks), and long-term effect (aggregated over 26 weeks), allowing us to distinguish transient vs. persistent effects.

The IRF results reinforce earlier analyses that brand heterogeneity exists in strategic actions, timing, and impact reflections. Figure 4 shows two sample IRF plots over the 26-week horizon. Plot (a) illustrates a long-lasting positive effect, where a BASOA shock remains impactful beyond 20 weeks. In contrast, Plot (b) demonstrates a transient effect, where the negative effect fades after a few weeks.

Tables 1 and 2 summarise the average immediate, short-term, long-term effects, and average horizons for the effects to reach the peak (wear-in) and fully dissipate (wear-out) across all brands for a shock administered at each of the four events. From Table 1, it is evident that the effects on ad awareness are positive on average for all events and all

Figure 4: IRF, Response = purchase intention, shock given at Black History Month 2021



(a) Absolut (b) Diet Coke

horizons shown. However, the effects on purchase intention show a mix of signs. While immediate effects of BASOA increase at these events tend to be negative, BASOA efforts around race-related events appear to have long-term benefits. One common observation across the two models is that the effects following BASOA shocks at the focal event of George Floyd's murder take longer to culminate and diminish.

Table 1: Average Effect of BASOA Shock on Ad Awareness

Event	Immediate	Short-term	Long-term	Wear-in	Wear-out
George Floyd's death	0.00021	0.00143	0.00331	2.09	8.96
Black History Month 2021	0.00082	0.00147	0.00281	1.62	6.77
Beginning of Chauvin's Trial	0.00037	0.00084	0.00185	1.74	6.46
Verdict against Chauvin	0.00063	0.00071	0.00169	1.57	5.68

Table 2: Average Effect of BASOA Shock on Purchase Intention

Event	Immediate	Short-term	Long-term	Wear-in	Wear-out
George Floyd's death	0.00006	0.00023	0.00007	1.43	6.18
Black History Month 2021	-0.00020	0.00002	0.00011	1.13	5.00
Beginning of Chauvin's Trial	-0.00013	0.00012	0.00010	1.11	4.75
Verdict against Chauvin	-0.00012	0.00005	-0.00008	0.90	3.89

4.4. Robustness checks

To validate our results, we conducted two robustness checks. First, we incorporated competition into the model. Firms may adjust racial representation efforts not only to address social issues but to enhance competitiveness through differentiation. Competition in BASOA is defined as the average BASOA level of all other brands in the industry, included as an additional endogenous variable. Second, we test broader racial representation by using the minority representation ratio, which includes all minority races in the numerator. The findings are consistent with those from the reported model.

5. Conclusion

This study explores the time-varying effects of Black actor representation in TV advertising on brand health metrics, leveraging a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to capture the dynamic interplay between representation and consumer responses. Using data from approximately 400 brands over a 104-week period surrounding George Floyd's death, we examine how the Black actor share of ads (BASOA) impacts ad awareness and purchase intention, revealing distinct temporal patterns and brand heterogeneity in these effects. By capturing the evolving nature of these effects, this research emphasizes the importance of considering both the timing of representation efforts and the objective of individual brands.

Our findings show that BASOA generally enhances ad awareness. These results highlight the importance of timing and societal context in amplifying the impact of representation efforts. In contrast, the effects of BASOA on purchase intention are more nuanced, with negative immediate impacts but positive long-term effects, suggesting a more complex path from representation to consumer behavior. Furthermore, our analysis reveals substantial brand heterogeneity, with certain brands benefiting more than others based on strategic actions and perceived sincerity.

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