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Does VAR Mitigate Finance-Driven Home Advantage? Evidence From the Turkish Super League[1]

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ABSTRACT

Whether Video Assistant Referee (VAR) tempers finance-driven home advantage is unclear. Using 1788 Turkish Super League matches (2017–18 pre-VAR; five post-VAR seasons excluding 2020–21), we estimate ordered logit models linking home outcomes to VAR, inflation-adjusted squad-value gaps and interactions. A decomposition separates talent-linked and residual finance. With financial parity, VAR's direct effect is negligible; for richer hosts, VAR progressively cuts the finance-driven home edge, reducing their odds of a better result by over one-third immediately and nearly one-half by 2023–24. This attenuation operates almost entirely through the talent channel: net of observed ability, finance still raises home success but with diminishing returns. VAR thus partially equalizes, narrowing but not closing financially driven disparities. Sustained competitive balance requires pairing video review with revenue sharing or spending caps.

Keywords: *Squad Value, Referee Bias, Competitive Fairness, VAR, Sports Regulations.*

VAR Finans Kaynaklı Ev Sahibi Avantajını Azaltıyor mu? Türkiye Süper Ligi'nden Kanıt

ÖZET

Bu çalışma, 2017–18 öncesi ve 2020–21 hariç VAR sonrası beş sezonu kapsayan toplam 1788 Süper Lig maçı üzerinden, Video Yardımcı Hakem'in (VAR) finans kaynaklı ev sahibi avantajını zayıflatıp zayıflatmadığını incelemektedir. Ev sahibi sonuçları, VAR, enflasyona göre düzeltilmiş kadro değeri farkları ve etkileşim terimleriyle ilişkilendirilerek sıralı logit modelleri tahmin edilmektedir. Ek olarak, finansın yetenekle ilişkili bileşeni ile artık bileşeni ayrıştırılmaktadır. Bulgular, finansal parite altında VAR'ın doğrudan etkisinin ihmal edilebilir düzeyde olduğunu; daha zengin ev sahibi takımlarda ise VAR'ın finans kaynaklı üstünlüğü kademeli biçimde azalttığını göstermektedir: daha iyi sonuç olasılığı başlangıçta üçte birden fazla, 2023–24'te ise neredeyse yarı yarıya düşmektedir. Bu zayıflama neredeyse bütünüyle yetenek kanalı üzerinden gerçekleşmektedir; gözlenen yetenek sabitken dahi finans ev sahibi başarısını artırmakta, ancak azalan getirilerle. Sonuç olarak, VAR kısmi bir eşitleyici işlevi görmekte; finansal eşitsizlikleri daraltmakta fakat ortadan kaldırmamaktadır. Kalıcı rekabet dengesi için video inceleme gelir paylaşımı ve/veya harcama tavanlarıyla desteklenmelidir.

Anahtar Kelimeler: *Kadro Değeri, Hakem Yanlılığı, Adil Rekabet, VAR, Spor Mevzuatı.*

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1. INTRODUCTION

Home advantage in soccer, defined as the tendency for teams to perform better at home than away, has been extensively documented across various leagues and seasons (Courneya & Carron, 1992; Nevill & Holder, 1999; Pollard, 1986; Pollard & Gómez, 2014). On average, home teams secure approximately 60% of the available points in league competitions worldwide (Leite, 2017; Liu, García-De-Alcaraz, Zhang, & Zhang, 2019; Peeters & van Ours, 2021). This persistent edge is commonly attributed to a confluence of factors, including fervent local support, officiating biases shaped by crowd pressure, venue familiarity, and travel fatigue for visitors (Nevill, Balmer, & Williams, 2002; Sors, Grassi, Agostini, & Murgia, 2021). While these factors account for much of the variance in home advantage, recent work identifies an additional dimension: financial power. This line of literature suggests that wealthier clubs enhance their home-field edge by leveraging larger, more intimidating stadiums, exerting off-field influence over league governance, and investing in superior training and recovery infrastructure to optimize match readiness (Bose, Feess, & Mueller, 2022; McCarrick, Bilalic, Neave, & Wolfson, 2021). These financial asymmetries, combined with fervent sell-out crowds, can intensify social pressure on officials, predisposing them to favor the home team on marginal calls, such as penalty awards and stoppage-time extensions (Garicano, Palacios-Huerta, & Prendergast, 2005; Ramchandani, Millar, & Wilson, 2021). If referees' marginal calls systematically tilt toward high-budget hosts, those clubs would record home results that exceed predictions based solely on ability differences. Demonstrating such a pattern would uncover an overlooked driver of home advantage and raise serious concerns about fairness and competitive balance.

This potential for financially driven home bias renders the introduction of the Video Assistant Referee (VAR) a pivotal development. By design, VAR subjects key incidents (goals, penalties, direct red cards, and mistaken identity) to impartial video review, a process intended to mitigate pressure from both intimidating crowds and influential clubs. Consequently, it should theoretically neutralize the disproportionate home advantage held by wealthier teams. Despite its theoretical promise to offset such biases, empirical studies have largely overlooked this specific financial dimension, focusing instead on VAR's general effect on home advantage. Even here, the findings are mixed. On the one hand, single-league European studies suggest that VAR does reduce home advantage. For instance, evidence from the German Bundesliga shows that key home-advantage metrics like points and goals decline and become insignificant post-VAR (Dufner, Schütz, & Hill, 2023). A joint study of the Italian and German top flights similarly finds that VAR partially reduces home bias in penalties, red cards, and stoppage-time allocation, though a residual advantage persists (Holder, Ehrmann, & König, 2022). On the other hand, broader evidence paints a different picture. A meta-analysis of over 9000 matches across twenty competitions uncovers no systematic shift in goals-based home advantage or score-line closeness after VAR's introduction (Rogerson et al., 2024). Likewise, studies from Turkey and broad cross-country settings conclude that VAR's primary impact is on disciplinary actions like

foul counts rather than point differentials or other key bias indicators (Abbate, Cross, & Uhrig, 2025; Işın & Yi, 2024). Taken together, the evidence is inconclusive regarding VAR's likely influence on home advantage and, crucially, silent on whether VAR curbs the finance-linked component of home advantage.

To address these gaps, we pose five research questions (RQs). Establishing a pre-VAR benchmark, we first ask whether financially stronger home teams enjoy a systematically larger advantage after controlling for team ability (RQ1) and whether the finance-performance relationship is nonlinear (RQ2). Turning to the VAR era, we investigate whether the technology alters home advantage when clubs are financially similar (RQ3) and whether its effect magnifies as the financial gap widens, distinguishing talent-mediated from other finance-related channels (RQ4). Finally, we adopt a longitudinal perspective to assess whether these direct and interactive effects evolve over time as referees, players, and supporters adapt to VAR (RQ5).

We ground our inquiry in the Turkish Super League, where the convergence of intense home crowds and pronounced financial disparities provides an ideal testing ground. The league's fervent supporters subject referees to extraordinary pressure and help home teams accrue 61.5% of available points,[5] surpassing the global average (Seçkin & Pollard, 2008). At the same time, economic inequality exceeds a tenfold range between the wealthiest and poorest clubs.[6] This combination creates a natural laboratory for assessing whether VAR's impact depends on club wealth, a question unanswerable in competitions lacking either pronounced financial disparities or intense supporter passion.

Our analysis provides what is, to our knowledge, the first league-level study to directly link VAR, club wealth, and home advantage in soccer. We measure teams' relative financial strength using the squad-market-value gap—a continuous proxy for economic distance that bundles expected on-field productivity with off-field resources and correlates with wage bills, transfer spending, revenues, and performance (Carmichael, McHale, & Thomas, 2011; Herm, Callsen-Bracker, & Kreis, 2014; Prockl & Frick, 2018; Quansah, Frick, Lang, & Maguire, 2021). To sharpen interpretation, we decompose this metric into (i) an observable talent component and (ii) a residual capturing infrastructure, commercial scale, and institutional leverage (see Section 2 for details). Our analysis of six seasons of Turkish Super League data, using ordered logit models, reveals three central findings. First, we confirm that financial strength confers a significant home-field edge that cannot be explained by team ability alone. Second, we find that VAR's impact is highly contingent on financial disparity: its direct effect on home advantage is marginal for financially comparable clubs, while it markedly attenuates the finance-driven edge enjoyed by the wealthiest clubs, though it does not eliminate it. Finally, in line with contest theory, we find that this financial influence is nonlinear, ultimately exhibiting diminishing marginal returns

[5] A Guinness World Record crowd noise of over 130 dB was recorded in an Istanbul derby (Janela, 2013).
[6] In the 2023–24 season, spending caps ranged from around 117 million TRY (e.g., Kasımpaşa) to nearly 1.48 billion TRY (e.g., Galatasaray) (Türkiye Futbol Federasyonu, 2023).

to wealth. A battery of diagnostic and specification tests confirms the validity of our model and, hence, the robustness of these findings.

These results have clear practical implications: technology can mitigate, but not eliminate, financially driven competitive imbalances. League administrators and refereeing bodies should therefore view VAR as a complement, not a substitute, for broader reforms such as revenue sharing, salary caps, or luxury taxes designed to foster parity. More generally, our evidence offers a crucial, data-driven perspective on the limits of technological solutions in financially stratified sports, providing a cautionary tale for governing bodies seeking a simple fix for deep-seated issues of competitive balance.

The remainder of the paper proceeds as follows. Section 2 describes the dataset and variable construction. Section 3 outlines the empirical strategy, including model specification and diagnostic checks. Section 4 presents the results and situates them within existing scholarship. Section 5 discusses theoretical and managerial implications, revisits the research questions, and concludes.

2. DATA

This study draws on six seasons of the Turkish Super League: the final pre-VAR season (2017–18) and five post-VAR seasons from the 2018–19 to 2023–24 period. To ensure a robust analysis of the interplay between technology-assisted officiating, club finances, and match outcomes, we restrict our sample to matches played under ordinary competitive conditions. The first set of exclusions removes matches played under COVID-19 restrictions, which include fixtures held behind closed doors. Specifically, we omit 82 fixtures staged after March 13, 2020, in the 2019–20 season; the entire 2020–21 calendar of 420 matches (all spectator-free); and 120 fixtures up to November 9, 2021, in the 2021–22 season. A second filter eliminates matches settled administratively: these include 29 matches from the 2022–23 season involving Gaziantep FK or Hatayspor, annulled following the February 6, 2023 earthquakes, and a single match in 2023–24 that was abandoned when Istanbulspor's president ordered his team off the pitch. After these adjustments, the final sample contains 1788 matches, which forms the basis for a series of estimations where each post-VAR season is separately pooled with the pre-VAR baseline. Table 1 documents the filtering process by season, indicating scheduled, excluded, and included fixtures, VAR status, and exclusion reasons.

Table 1. Match Counts by Season, VAR Status, and Reason for Exclusion

Season	VAR status	Scheduled	Excluded	Included	Reasons for exclusion
2017–18	Absent	306	0	306	–
2018–19	Present	306	0	306	–
2019–20	Present	306	82	224	COVID-19 restrictions
2020–21	Present	420	420	0	COVID-19 restrictions

2021–22	Present	380	120	260	COVID-19 restrictions
2022–23	Present	342	29	313	Earthquake
2023–24	Present	380	1	379	Abandoned
Total	–	2440	652	1788	–

Note. See Tables 2, 3, and A2 for the number of observations used in each estimation. Match data, including results, dates, and special circumstances are compiled from the Turkish Football Federation's website tff.org.

Having established our clean sample, we now define the two core predictors, financial and ability differentials, that underpin our econometric models. Relative financial strength in match i is captured by the financial differential, $FinDif_i$, calculated as the difference between the inflation-adjusted squad valuations of the home and away teams. To facilitate inter-season comparability, each team's nominal squad value (retrieved from transfermarkt.com and scaled in €100 million units) is adjusted to constant August 2024 euros by deflating with Eurostat's Harmonized Index of Consumer Prices (HICP; 2015=100; series code PRC_HICP_MIDX) and then rebasing the resulting series.[7] Formally, let $SV_{i,j}^{\text{nominal}}$ denote the nominal squad value for team $j \in \{\text{ho}, \text{aw}\}$ in match i, with ho and aw signifying the home and away sides, respectively. The real (inflation-adjusted) value is computed as

$$SV_{i,j}^{\text{real}} = \left(\frac{SV_{i,j}^{\text{nominal}}}{100 \text{ million}}\right) \times \left(\frac{\text{HICP}_{\text{Aug 2024}}}{\text{HICP}_{\text{Aug Season}}}\right)$$

, where $\text{HICP}_{\text{Aug Season}}$ is the index value for August of the relevant season. With valuations standardized to August 2024 euros, the financial differential becomes

$$FinDif_i = SV_{i,\text{ho}}^{\text{real}} - SV_{i,\text{aw}}^{\text{real}}. \quad (1)$$

Accordingly, each one-unit increment in $FinDif_i$ corresponds to a €100 million advantage in squad value for the home team. We capture relative ability directly from pre-match Elo ratings (sourced from elofootball.com). Letting $Elo_{i,\text{ho}}$ and $Elo_{i,\text{aw}}$ represent the home and away teams' Elo ratings immediately prior to match i, we define the ability differential as

$$AbDif_i = \frac{Elo_{i,\text{ho}} - Elo_{i,\text{aw}}}{100}. \quad (2)$$

Thus, each unit indicates a 100-point Elo advantage for the home side. The normalization of both financial and ability differentials ensures interpretability of regression coefficients.

[7] See Appendix Table A1 for the specific Harmonized Index of Consumer Prices (HICP) values and the inflation-adjustment factors used for each season. Expressing all financial figures in constant August 2024 euros aligns all financial data with the most recent league calendar at the time of writing, enhancing both comparability across seasons and practical relevance.

Two primary considerations underlie our choice of $FinDif_i$ and $AbDif_i$ as key predictors. First, season-specific squad valuations, aggregated from individual player market values, are widely acknowledged as reliable indicators of a club's financial capacity and cumulative talent. Large-sample evidence shows that squad value tracks club revenues and wage expenditure almost one-for-one (Pérez-González, de la Riva, Bonal, & Fernández-Luna, 2020) and that it is the single most powerful predictor of league performance across Europe's top divisions (Gerhards & Mutz, 2017; Metelski, 2023). Given that player market values inherently incorporate age, ability, potential, and current form (Tunaru & Viney, 2010), squad-value gaps robustly represent disparities in both financial strength and overall quality. Second, Elo ratings are updated after each fixture based on the match result and the relative ratings of the opponents, thereby blending recent performance with long-term reputation. Empirical studies demonstrate that pre-match Elo differentials outperform alternative ranking systems in forecasting match outcomes (Hvattum & Arntzen, 2010; Lasek, Szlávik, & Bhulai, 2013). Although no performance metric is perfectly exogenous to a club's resources, pre-match Elo ratings are widely considered the most effective dynamic proxy for a team's current competitive strength. Therefore, utilizing the normalized pre-match Elo differential ($AbDif_i$) as the real-time proxy for relative team strength alongside the $FinDif_i$ measure allows us to disentangle talent-driven success from residual financial effects. This approach clarifies how VAR interacts with both economic and ability-related dimensions of competitive strength in the subsequent analysis.

3. METHODOLOGY

Given that match outcomes are inherently ordinal (loss < draw < win), we adopt an ordered logit framework. Our empirical strategy evaluates the impact of financial resources on home advantage through a sequence of three models that offer a progressively more nuanced perspective: Gross-Finance (GF), Ability-Controlled-Finance (ACF), and Net-Finance (NF) models. Central to this framework is a latent variable Y_i^* that formulates the home team's underlying propensity for a more favorable result in match i. The observed outcome takes the value "loss," "draw," or "win" according to whether Y_i^* falls below, between, or above two estimated thresholds. Mathematically, each specification is represented as follows:

$$\text{GF:} \quad Y_i^* = \beta_1 VAR_i + \beta_2 FinDif_i + \beta_3 FinDif_i^2 + \beta_4 (VAR_i \times FinDif_i) + \epsilon_i \tag{3}$$

$$\text{ACF:} \quad Y_i^* = \beta_1 VAR_i + \beta_2 FinDif_i + \beta_3 FinDif_i^2 + \beta_4 (VAR_i \times FinDif_i) \tag{4}$$

$$\text{NF:} \quad Y_i^* = \beta_1 VAR_i + \beta_2 FinRes_i + \beta_3 FinRes_i^2 + \beta_4 (VAR_i \times FinRes_i) \tag{5}$$

, where the error term ϵ_i follows a standard logistic distribution. In these formulations, VAR_i is a binary indicator that equals 1 if the VAR system was operational and 0 otherwise. As defined in Equations (1) and (2), the financial differential $FinDif_i$ is the home-minus-away squad-value gap (in €100 million units), and the ability differential $AbDif_i$ is the pre-

match Elo rating gap (in 100-point units). Lastly, we define $FinRes_i$ as the residual ε_i from the season-specific OLS regression specified in Eq. (6).

$$FinDif_i = \alpha + \beta AbDif_i + \varepsilon_i. \quad (6)$$

By construction, ε_i captures the component of the home team's financial advantage that is uncorrelated with its on-field ability.

These models sequentially disentangle the channels through which financial resources influence home advantage. In the baseline GF model (Eq. 3), $FinDif_i$ serves as an omnibus proxy for club resources. As previously motivated, it embodies both spending capacity, measured via aggregated player market prices that closely track revenues and wages, and the advantages conferred by on-field quality and off-field assets. The ACF model (Eq. 4) augments this baseline by incorporating the Elo rating differential $AbDif_i$ to separate the effect of on-field ability from other financial influences. While this augmentation offers a more refined view, the high correlation between squad value and team ability inflates the standard errors of the estimates. To overcome this multicollinearity, the third and final specification, the NF model (Eq. 5) replaces the raw financial differential ($FinDif_i$) with its residual component ($FinRes_i$) in the ACF. Put differently, the NF model focuses on off-field assets (e.g., training facilities, analytics departments, political clout) that are statistically orthogonal to ability. Nevertheless, as a residual component, $FinRes_i$ may also absorb other unobserved factors not fully captured by our ability metric, such as specific coaching tactics or measurement error.

Model coefficients are interpreted as follows. Across all three specifications, β_1 quantifies VAR's impact (in log-odds) at financial parity (when financial differential or residuals are zero). Exponentiating β_1 yields the odds ratio $exp(\beta_1)$, representing how VAR influences the odds of achieving at least a "no-loss" (draw or win) and, due to the proportional-odds assumption, the odds of securing a "win" when VAR is active, at financial parity (i.e., $FinDif_i = 0$ or $FinRes_i = 0$). For instance, an odds ratio of 1.20 amounts to a 20% increase in the odds of a more favorable home outcome under VAR at financial parity. The coefficients β_2 and β_3 trace how the financial gap affects outcomes in a no-VAR setting, with β_3 capturing curvature such that positive values indicate increasing returns to finance, negative values suggest diminishing returns. Crucially, the interaction coefficient β_4 reveals whether VAR mitigates or amplifies the finance-performance relationship. Finally, in the ACF and NF models, β_5 is the proportional-odds effect of a 100-point Elo advantage, conditional on the specified financial variables.

To enhance interpretability, we transform the log-odds coefficients into marginal effects on outcome probabilities. More precisely, we calculate the predicted probability changes for no-loss and win outcomes as VAR_i switches from 0 to 1, evaluating these effects at strategic points of the financial disparity distribution: the minimum, 25th percentile,

financial parity, 75th percentile, and maximum. This clarifies how VAR's influence shifts across varying levels of financial disparity.

To investigate potential adaptation effects over time, we perform a dynamic, season-by-season analysis. Specifically, for each season after VAR's implementation, we estimate Equations (3)–(5) using a two-season sample combining that post-VAR season with the 2017–18 season, which serves as our consistent pre-VAR benchmark. Accordingly, the VAR indicator varies only across the two seasons in each specification. The observation counts reported in subsequent tables are therefore the sum of matches from the pre-VAR season and the indicated post-VAR season. For example, the analysis for the 2018–19 season uses 612 matches (306 + 306), the 2019–20 season uses 530 matches (306 + 224), and so on. This exercise enables us to trace the evolution of the key coefficient estimates following VAR's introduction.

Model diagnostics confirm robustness. Goodness-of-fit, assessed via McFadden pseudo-R^2, AIC, BIC, and likelihood-ratio tests against intercept-only models, demonstrate substantial explanatory power improvements over null specifications (Table A2). Variance-inflation factors are comfortably below critical thresholds except in the expected cases within the ACF model (Table A3). The proportional-odds assumption is not rejected using Stata's gologit2 test (Table A4), with all global chi-squared tests yielding p-values well above conventional significance thresholds (all $p > 0.10$). All reported coefficients employ robust (HC1) standard errors, and estimations (excluding proportionality tests) are conducted in Python (StatsModels), with data management facilitated by Pandas.[8]

4. FINDINGS AND INFERENCE

Using the three ordered-logit specifications introduced in Section 3, the Gross-Finance (GF), Ability-Controlled-Finance (ACF), and Net-Finance (NF) models, we now answer the five research questions (RQ1–RQ5) posed in the Introduction. We organize the estimation results into three tables: Table 2 details the coefficients for finance and ability variables; Table 3 presents the estimates for the VAR term and its interaction with finance; and Table 4 translates these findings into practical terms, displaying the marginal effects of VAR on match outcome probabilities at key financial disparity benchmarks. Together, these outputs trace how VAR and financial disparity have shaped home advantage from 2018–19 to 2023–24, benchmarked against the 2017–18 pre-VAR season. Throughout, robust (HC1) standard errors appear in parentheses; *, **, and *** mark significance at the 10%, 5%, and 1% levels, respectively. Models are labeled GF, ACF, and NF.

Our analysis first addresses RQ1 and RQ2 by examining the standalone effect of relative financial power in the absence of VAR. In response to RQ1 (Does wealth confer an advantage beyond talent?), the results in Table 2 show unequivocally that it does. The coefficient on the financial differential (β_2 in Table 2) is significant across all models and

[8] The Python code used in this study is available from the corresponding author upon request.

seasons. In the GF specification, it ranges from 1.46 to 1.64 (all $p < 0.001$), implying that each additional €100 million of squad value increases the odds of a better home result by 4.3 to 5.2. Introducing team ability in the ACF model attenuates β_2 by about one-third, bringing it down to a range of 0.77–1.27 (all $p < 0.01$), still equivalent to doubling or tripling of the odds (2.2–3.6), with the effect remaining robust across seasons.[9] More to the point, even after orthogonalizing finance against ability in the NF model, β_2 still lies between 1.07 and 1.13 (all $p < 0.05$), a residual premium that nearly triples the odds of a favorable home outcome. These cross-model declines demonstrate that, although on-field talent mediates a substantial share of the finance premium, a significant independent effect persists, most plausibly reflecting off-field investments in elite coaching, tactical analytics, sports science, and squad depth that help clubs absorb injuries and fixture congestion.

Table 2. Finance and Ability Effects on Home-Match Outcomes

Model	Variable (β)	2018–19	2019–20	2021–22	2022–23	2023–24
GF	$FinDif_i$ (β_2)	1.64*** (0.28)	1.64*** (0.28)	1.51*** (0.25)	1.46*** (0.25)	1.53*** (0.26)
	$FinDif_i^2$ (β_3)	0.50** (0.21)	0.53** (0.26)	0.16 (0.16)	-0.04 (0.12)	0.00 (0.07)
ACF	$FinDif_i$ (β_2)	1.27*** (0.36)	1.06*** (0.40)	0.77** (0.35)	1.01*** (0.35)	1.06*** (0.36)
	$FinDif_i^2$ (β_3)	0.49** (0.20)	0.53** (0.26)	0.15 (0.16)	-0.05 (0.12)	-0.01 (0.07)
	$AbDif_i$ (β_5)	0.13 (0.08)	0.21** (0.10)	0.27*** (0.09)	0.16* (0.09)	0.17* (0.09)
NF	$FinRes_i$ (β_2)	1.07*** (0.41)	1.10*** (0.43)	1.08*** (0.42)	1.07** (0.42)	1.13** (0.44)
	$FinRes_i^2$ (β_3)	0.63 (0.49)	0.58 (0.97)	0.07 (0.41)	-0.64** (0.29)	-0.43 (0.40)
	$AbDif_i$ (β_5)	0.38*** (0.05)	0.44*** (0.06)	0.45*** (0.06)	0.46*** (0.06)	0.50*** (0.05)
Obs.		612	530	566	619	685

Note. $FinDif_i$ = home-away squad-value gap (€100m); $AbDif_i$ = home-away ability gap (100-point Elo scale) $FinRes_i$ = residual of $FinDif_i$ orthogonal to $AbDif_i$.

Regarding RQ2 (Is the finance-performance link nonlinear?), the evidence is dynamic and answers a part of RQ5 (Do effects evolve over time?). In the first two post-VAR seasons (2018–19 and 2019–20), the quadratic finance term is positive and significant ($\beta_3 \approx 0.50$), indicating increasing marginal returns to financial superiority. However, from the 2021–22

[9] Season-by-season reductions in β_1 from GF to ACF are 22.6%, 35.4%, 49.0%, 30.8%, and 30.7%, which average 33.7%.

season onward, this effect diminishes, becoming insignificant or even negative. This is most apparent in the NF model, which isolates off-field spending, where the coefficient turns significantly negative in 2022–23 ($\beta_3 = -0.64, p < 0.05$). This reversal suggests a shift toward diminishing marginal returns, consistent with contest theory predictions that additional spending yields smaller competitive gains.[10] The lack of robustness over time underscores that the nonlinear finance effect is sensitive to evolving competitive dynamics rather than a stable feature of the finance-performance relationship. One plausible explanation is that the initial advantages from pioneering investments in analytics and sports science may have eroded as these practices become widespread. Alternatively, this trend may reflect a broader strategic adaptation by clubs to the new technological environment, or simply a natural stabilization of the finance-performance relationship over a longer period.

Next, we turn to RQ3 (How does VAR alter home advantage for financially similar clubs?), Table 3 unveils a remarkably uniform result across all three specifications. The coefficient on the VAR indicator (β_1) is consistently small and negative in all seasons but generally insignificant. Notably, this lack of a significant VAR impact persists uniformly over time, speaking to RQ5. The sole exception is the 2019–20 season, when β_1 reaches marginal significance ($p < 0.10$), estimated at -0.32 in the GF model and -0.33 in both the ACF and NF models. This implies a 27% to 28% fall in the odds of a better home outcome (i.e., an odds ratio of $exp(-0.32) \approx 0.73$ and $exp(-0.33) \approx 0.72$), albeit with only weak statistical support. The parallel in estimates across specifications is unsurprising. As teams' financial power converges, so too do their abilities and, therefore, controlling for talent (ACF) or residualizing finance (NF) adds little beyond the raw Gross-Finance (GF) specification.

Several elements may underlie this muted direct effect. One interpretation is that VAR may mitigate refereeing decisions influenced by institutional pressures. In matches where neither side possesses a significant financial advantage, these external pressures are likely already diminished, potentially leaving less scope for VAR to alter the dynamics of officiating and, consequently, the outcome. Another key consideration is the limited scope of VAR itself. The technology is designed to correct only clear and obvious errors, such as incorrectly awarded goals or missed red-card offenses. Subtler aspects of officiating, such as applying advantage, determining the precise placement of free kicks, and general game management, remain susceptible to crowd influence and fall outside VAR's purview. Finally, classic elements of home advantage persist, seemingly untouched by video review: the psychological boost from home supporters, the comfort of a familiar pitch, and the visiting team's travel fatigue. In contests where financial parity already suggests a close match, these psychological and physiological elements could plausibly outweigh any incremental gains in fairness that VAR is able to deliver.

[10] Our observed shift from increasing to diminishing returns mirrors the S-shaped Tullock success function when the effort exponent, r, exceeds 1, unlike the purely concave form (only diminishing returns) when $r \leq 1$.

Table 3. VAR Effects on Home-Match Outcomes (GF, ACF, and NF Models)

Model	Variable (β)	2018–19	2019–20	2021–22	2022–23	2023–24
GF	VAR_i (β_1)	-0.14 (0.16)	-0.32* (0.17)	-0.26 (0.17)	-0.25 (0.16)	-0.11 (0.15)
	$VAR_i \times FinDif_i$ (β_4)	-0.60* (0.35)	-0.37 (0.40)	-0.70** (0.31)	-0.53* (0.20)	-0.49* (0.29)
ACF	VAR_i (β_1)	-0.14 (0.16)	-0.33* (0.70)	-0.27 (0.17)	-0.25 (0.16)	-0.11 (0.15)
	$VAR_i \times FinDif_i$ (β_4)	-0.51 (0.35)	-0.30 (0.39)	-0.38 (0.32)	-0.31 (0.31)	-0.30 (0.31)
NF	VAR_i (β_1)	-0.12 (0.16)	-0.33* (0.17)	-0.25 (0.17)	-0.20 (0.16)	-0.10 (0.16)
	$VAR_i \times FinRes_i$ (β_4)	-0.33 (0.51)	-0.64 (0.68)	-0.95* (0.50)	-0.45 (0.48)	-0.45 (0.49)
Obs.		612	530	566	619	685

Note. Financial variables are measured in €100 million units.

Regarding RQ4 (How does VAR's impact scale with financial disparity?), the interaction coefficient (β_4 in Table 3) gauges whether VAR moderates the performance premium that accrues to high-budget home teams. In the baseline Gross-Finance (GF) model, β_4 is negative across all seasons and is statistically significant (at 10% or 5%) in all periods except for 2019–20. Its point estimates range from -0.37 to -0.70. In economic terms, for each €100 million of squad-value advantage, VAR trims the log-odds of a superior home result by roughly 0.5–0.7, which is equivalent to lowering the odds of that outcome by 39–50%. Once observable ability is held constant (ACF) or finance is purged of its ability component (NF), this dampening effect weakens markedly. In the ACF model, β_4 falls roughly by one-third to one-half in size relative to GF; more importantly, none of these coefficients reach statistical significance ($p > 0.10$ throughout). In the NF model, the pattern is even starker: although the point estimates grow in magnitude (e.g., -0.64 in 2019–20 and -0.95 in 2021–22), imprecision increases (standard errors double in magnitude), so significance again evaporates. This stark loss of significance when controlling for talent reveals a critical insight: VAR's power to neutralize financial advantage operates almost exclusively through the on-field talent channel. Once a team's current ability is statistically separated from its financial muscle (in the ACF and NF models), VAR's interactive effect vanishes. This indicates that VAR primarily works by correcting the types of decisive, on-field incidents that superior players are more likely to create, rather than mitigating the off-field advantages that money buys (e.g., better infrastructure, stadium quality, or analytics).

Several explanations might contribute to this result. First, VAR places decisive, match-altering moments under a microscope. Financially powerful clubs are often better able to acquire faster, more inventive forwards who are more likely to create borderline situations,

including plays that are marginally offside, involve slight contact in the penalty area, or draw fouls through skillful exaggeration. Before VAR, referees may have been more inclined to give the benefit of the doubt to the home team, supported by a fervent crowd. Slow-motion review reduces this margin for discretion. Consequently, the attacking flair bought by large budgets may not translate as reliably into favorable calls. Second, VAR can help mitigate reputation bias. It is often suggested that high-status, wealthy clubs have historically benefited from a subtle officiating edge rooted in their prestige. By requiring major decisions to be backed by visual evidence rather than perception or institutional weight, video review can strip away much of the intangible authority that financial power once conferred on the pitch. Lastly, VAR does not address the performance advantages that flow from off-field investments. Financially dominant clubs continue to benefit from superior medical teams that keep players fitter, advanced analytics departments that inform strategy, and modern stadiums that optimize playing surfaces and amplify crowd energy.

The marginal effects in Table 4, which are derived from the GF model, illustrate this dynamic in practical terms. Each cell shows changes in probabilities of achieving no-loss or win outcomes (in percentage points) when VAR is introduced, evaluated at five levels of financial differential: Min (minimum), Q_1 (first quartile; 25th percentile), Parity (0), Q_3 (third quartile; 75th percentile), and Max (maximum). Standard errors (in parentheses) are obtained from 500 parametric bootstrap draws of the ordered-logit coefficient vector, simulated from its joint asymptotic multivariate normal distribution. At each draw, we recompute the marginal effects; the empirical standard deviation of these replications provides a consistent bootstrap standard error for the nonlinear functions of the parameters (Cameron & Trivedi, 2005, pp. 253–255, 412–417;Greene, 2023, pp. 699–700). Results for the ACF and NF models appear in Tables A5 and A6.

Table 4. Marginal Probability Effects of VAR by Financial Differential (GF Model)

	2018–19		2019–20		2021–22		2022–23		2023–24	
$FinDif_i$	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win
Min	28.80*	30.70*	13.88	13.51	29.55**	15.14	9.40	3.46	11.55	3.51
(-2.48)	(15.93)	(15.93)	(16.71)	(16.13)	(13.94)	(11.60)	(7.31)	(3.55)	(7.71)	(2.97)
Q_1	0.35	0.36	-5.30	-5.12	-1.69	-1.75	-2.56	-2.67	0.49	0.52
(-0.26)	(3.55)	(3.68)	(3.94)	(3.67)	(3.84)	(3.94)	(3.77)	(3.88)	(3.31)	(3.56)
Parity	-2.76	-3.44	-6.73**	-7.90**	-5.20	-6.35	-5.01	-6.21	-1.94	-2.58
(0)	(2.92)	(3.61)	(3.30)	(3.73)	(3.29)	(3.90)	(3.27)	(3.94)	(2.71)	(3.57)
Q_3	-4.79	-7.42	-7.14**	-10.52**	-7.67**	-11.03**	-6.67**	-9.72**	-3.58	-5.88
(0.27)	(2.92)	(4.53)	(3.45)	(5.00)	(3.24)	(4.62)	(3.19)	(4.59)	(2.63)	(4.31)
Max	-0.11	-0.39	-0.06	-0.19	-1.89	-5.68	-4.08	-11.30	-1.86	-6.82
(2.48)	(0.72)	(2.30)	(0.79)	(2.18)	(4.10)	(8.67)	(3.58)	(7.99)	(1.77)	(5.57)

Note. Entries are percentage-point changes in predicted probabilities of no-loss and win outcomes when VAR_i switches from 0 to 1, evaluated at five values of $FinDif_i$ (in €100m). Parentheses report standard errors, except in the first column, where they instead report the $FinDif_i$ evaluation points. The sample median is virtually identical to Parity and is therefore omitted.

For the most financially disadvantaged ("underdog") home teams ($FinDif_i$=Min), VAR confers a substantial protective benefit. This effect is not only large but often statistically significant. For example, in 2018–19, VAR increases the win probability for the weakest hosts by a significant 30.70 percentage points ($p<0.10$). A similarly strong and significant effect is seen in 2021–22, with a 29.55-point increase in the probability of a no-loss outcome ($p<0.05$). This large protective effect is a direct consequence of the negative interaction between VAR and finance (β_4), confirming that VAR acts as a shield for underdogs by neutralizing the talent-driven advantages of their far wealthier opponents, likely by overturning the borderline goals, penalties, and other decisive incidents that superior talent creates. At financial parity ($FinDif_i = 0$), where the powerful influence of financial disparity is removed, VAR imposes a small and consistent disadvantage on the home team. In the 2019–20 season, this effect is statistically significant, reducing the probability of a win by 7.90 percentage points ($p<0.05$). In other seasons, the effect is smaller and not statistically distinguishable from zero. This effect directly corresponds to the main VAR coefficient (β_1) from Table 3. With the powerful influence of financial disparity removed, we are left with VAR's baseline tendency to more strictly penalize home-team infractions, chipping away at the traditional home advantage unrelated to finance. The results at the first quartile (Q_1) fall between these two extremes (Min and parity), showing a small negative impact in most seasons. For wealthy home clubs ($FinDif_i \geq Q_3$), VAR imposes a statistically robust and economically meaningful liability. In three consecutive seasons from 2019–20 to 2022–23, VAR significantly reduces the win probability for these clubs, with effects ranging from -9.7 to -11.0 percentage points (all $p<0.05$). This is the mirror image of the underdog effect and is again explained by the significant negative interaction term (β_4). It demonstrates that as the video-review regime has matured, VAR has become more effective at eroding the on-field advantages that money buys, disciplining the very teams whose superior talent would have otherwise benefited from favorable calls.

Collectively answering RQ4, these findings show that over six seasons, VAR has evolved from a simple officiating tool into a broader equalizer, with its influence contingent on the financial context of the match. At strict financial parity, VAR's direct influence is minimal; however, as soon as budgets diverge, its role becomes critical. The results from Table 3 show that VAR's primary mechanism is to neutralize the on-field advantages of talent-intensive spending. Indeed, the broader moderating effects seen in Table 4 become smaller and largely insignificant once on-field ability is explicitly controlled for (Tables A5 and A6), confirming that VAR's equalizing power operates almost exclusively through this talent channel. At the same time, the findings from Table 3 reveal that the immense power of money continues to operate off-field through superior coaching, infrastructure, and squad depth, even if the on-field returns may now be diminishing. The marginal effects in Table 4 are the net result of this dynamic: VAR protects the weakest clubs by reining in the talent of the strongest, thereby flattening the finance-performance gradient. Nonetheless, it cannot erase the entrenched structural asymmetries that wealth confers. Policymakers,

therefore, should not treat VAR as a panacea. Sustained competitive balance requires a dual approach: leveraging technology like VAR to ensure on-field fairness while implementing robust financial regulations (for example, spending caps and revenue sharing) to address the deeper economic imbalances that technology alone cannot solve.

5. CONCLUSION

This study investigated how Video Assistant Referee (VAR) technology interacts with club-level financial disparity and home advantage in the Turkish Super League. Using match-level data from one pre-VAR season (2017–18) and five post-VAR seasons (2018–19 through 2023–24, omitting 2020–21 because of COVID-19 disruptions), we estimated a sequence of ordered-logit models—Gross-Finance (GF), Ability-Controlled-Finance (ACF) and Net-Finance (NF)—to disentangle talent-linked and off-field components of spending. We find that financial power matters: the larger the home club's squad-value edge, the higher its probability of avoiding defeat or securing a win.

VAR alone matters little: once financial parity is imposed, VAR's standalone influence on home advantage is small and rarely significant. The central result, however, concerns the interaction of VAR with wealth. VAR consistently reduces the extra home-field edge enjoyed by financially stronger clubs, and this moderating influence becomes clearer with each passing season. When we partition spending into talent-linked (ACF) and residual (NF) components, the VAR × wealth term remains significant only for the talent component, indicating that VAR mainly neutralizes advantages that flow through superior on-field personnel rather than through stadium infrastructure, analytics departments or other off-pitch assets. Marginal-effect calculations corroborate this pattern: underdogs gain meaningful probability boosts while favorites surrender a slice of their dominance whenever VAR is active. These shifts amount to roughly 10–30 percentage points for underdogs and 5–11 points in reduced win probability for the wealthiest clubs. This pattern parallels the league-level evidence from Germany and Italy that VAR attenuates, rather than eliminates, traditional home-bias channels (Dufner et al., 2023; see also Holder et al., 2022), and it helps reconcile meta-analytic null results by showing that average unconditional impacts can mask sizable effects that arise when budgets diverge (Rogerson et al., 2024). Our findings also complement recent studies for Turkey and cross-country settings that emphasize discipline-related outcomes over points (Abbate et al., 2025; Işın & Yi, 2024): our estimates indicate that once financial gaps are wide, result-level probabilities do shift, chiefly via talent-mediated incidents.

Despite this moderation, financial power itself remains a robust predictor of success. Large squad-value gaps still translate into higher home-match odds, although the early-period accelerating returns detected in the GF model flatten out in later seasons and virtually disappear once talent is explicitly accounted for in ACF and NF. This flattening may reflect strategic adaptation by clubs and officials, diminishing marginal returns to expenditure, or both.

Taken together, the evidence shows that VAR functions as a partial equalizer: it curtails the channel through which money buys officiating-sensitive advantages, yet it does not erase the broader competitive edge conferred by superior budgets. Policymakers should therefore treat VAR as a complement rather than a substitute for structural reforms (such as revenue sharing, spending caps, or luxury-tax mechanisms) that address underlying fiscal asymmetries. In heavily imbalanced leagues, coupling VAR with stricter financial-fair-play enforcement could yield a more level playing field without undermining the entertainment value of elite football. For instance, leagues could explore dynamic spending caps where the ratio of the highest to lowest team budget is not permitted to exceed a fixed threshold (e.g., 5:1), a system VAR could help support by ensuring results more closely reflect true ability rather than officiating bias.

Future research could test whether these Turkish-league dynamics generalize to competitions with different ownership models, revenue structures, or VAR protocols. Panel data spanning additional seasons would help determine whether the moderating effect stabilizes, grows, or wanes over longer horizons. A finer-grained look at which specific review types (for example, penalty checks versus offside calls) most effectively curb talent-driven advantages would further aid administrators in designing transparent, competitively balanced, and commercially attractive football competitions.

APPENDIX

Table A1. Euro-Area HICP (August) and Inflation-Adjustment Factors (Base = Aug 2024)

Season	Index period	HICP (2015=100)	Inflation-adjustment factor
2017–18	Aug 2017	101.89	1.24
2018–19	Aug 2018	104.01	1.22
2019–20	Aug 2019	105.06	1.21
2021–22	Aug 2021	107.98	1.17
2022–23	Aug 2022	117.85	1.08
2023–24	Aug 2023	124.03	1.02

Note. Inflation-adjustment factors convert nominal squad values into constant August 2024 euros by referencing the Euro-area Harmonized Index of Consumer Prices (HICP) for August of each season (Aug 2015 = 100). Formally, for the season starting in year t: $\text{Inflation} - \text{adjustment factor}_t = \text{HICP}_{\text{Aug 2024}}/\text{HICP}_{\text{Aug t}}$ with $\text{HICP}_{\text{Aug 2024}} = 126.72$. Data are drawn from Eurostat's PRC_HICP_MIDX (filter combination M, I15, CP00, EA).

Table A2. Model Fit Diagnostics by Season and Model

Season	Obs.	Model	Log-likelihood	McFadden's R^2	AIC	BIC	LR χ^2
2018–19	612	GF	-606.78	0.06	1225.56	1252.06	75.72
		ACF	-605.52	0.06	1225.04	1255.96	78.24

		NF	-608.84	0.06	1231.68	1262.60	71.60
		GF	-524.97	0.07	1061.95	1087.58	74.07
2019–20	530	ACF	-522.74	0.07	1059.47	1089.38	78.54
		NF	-524.57	0.07	1063.15	1093.06	74.87
		GF	-562.47	0.06	1136.94	1162.97	65.81
2021–22	566	ACF	-558.14	0.06	1130.28	1160.65	74.46
		NF	-557.49	0.06	1128.98	1159.35	75.76
		GF	-602.65	0.07	1217.29	1243.86	94.40
2022–23	619	ACF	-601.02	0.08	1216.04	1247.03	97.66
		NF	-598.94	0.08	1211.89	1242.89	101.80
		GF	-658.28	0.09	1328.56	1355.74	127.04
2023–24	685	ACF	-656.53	0.09	1327.06	1358.76	130.54
		NF	-656.76	0.09	1327.52	1359.22	130.08

Note. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. The likelihood-Ratio (LR χ^2) test compares each model against an intercept-only specification. Degrees of freedom are 4 for GF and 5 for ACF/NF. All LR χ^2 statistics are significant at $p < 0.001$.

Table A3. Variance-Inflation Factors (VIFs) by Season and Model

Model	Predictor	2018–19	2019–20	2021–22	2022–23	2023–24
GF	VAR_i	1.00	1.01	1.02	1.08	1.07
	$FinDif_i$	2.11	1.59	2.30	3.81	5.15
	$FinDif_i^2$	1.00	1.01	1.02	1.08	1.07
	$VAR_i \times FinDif_i$	2.11	1.59	2.30	3.81	5.15
ACF	VAR_i	1.00	1.00	1.02	1.08	1.07
	$FinDif_i$	4.66	4.27	5.71	9.10	12.37
	$FinDif_i^2$	1.00	1.01	1.02	1.08	1.07
	$VAR_i \times FinDif_i$	2.18	1.61	2.65	4.79	6.16
	$AbDif_i$	3.01	3.44	3.11	3.36	4.38

NF	VAR_i	1.02	1.01	1.06	1.07	1.06
	$FinRes_i$	2.49	1.61	2.75	4.02	3.58
	$FinRes_i^2$	1.02	1.01	1.07	1.08	1.07
	$VAR_i \times FinRes_i$	2.50	1.61	2.77	4.03	3.59
	$AbDif_i$	1.00	1.00	1.00	1.00	1.00

Note. Variance-inflation factors (VIFs) measure multicollinearity, with values over 10 often indicating a problem. While the GF and NF models show no cause for concern, the ACF model's $FinDif_i$ predictor has a high VIF, peaking at 12.37 in 2023–24, thereby suggesting potential coefficient instability. This, however, is expected given the strong correlation between $FinDif_i$ and $AbDif_i$.

Table A4. Parallel-Lines (Proportional-Odds) Test Statistics (χ^2) by Season and Model

Model	2018–19	2019–20	2021–22	2022–23	2023–24
GF	3.09 (0.54)	1.62 (0.80)	1.42 (0.84)	4.35 (0.36)	7.25 (0.12)
ACF	3.35 (0.65)	1.77 (0.88)	3.35 (0.65)	5.10 (0.40)	8.34 (0.14)
NF	4.28 (0.51)	2.70 (0.75)	4.13 (0.53)	2.01 (0.85)	1.97 (0.74)

Note. Global χ^2 tests for the parallel-lines assumption using Stata's gologit2 routine. P-values are in parentheses. Degrees of freedom are 4 for GF and 5 for ACF/NF. In all cases, failure to reject the null hypothesis indicates the proportional-odds assumption holds.

Table A5. Marginal Probability Effects of VAR by Financial Differential (ACF Model)

	2018–19		2019–20		2021–22		2022–23		2023–24	
$FinDif_i$	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win
Min (-2.48)	17.07 (15.35)	27.27* (16.55)	4.71 (13.64)	9.03 (16.63)	15.99 (15.69)	14.44 (14.64)	7.98 (11.56)	3.34 (6.28)	11.62 (12.10)	4.30 (6.16)
Q_1 (-0.26)	-0.12 (3.61)	-0.13 (3.93)	-5.67 (4.36)	-5.93 (4.39)	-3.59 (3.82)	-4.07 (4.21)	-3.79 (3.89)	-4.15 (4.22)	-0.59 (3.33)	-0.68 (3.79)
Parity (0)	-2.73 (3.09)	-3.41 (3.81)	-6.85* (3.68)	-8.03* (4.10)	-5.36 (3.55)	-6.57 (4.16)	-5.06 (3.38)	-6.27 (4.08)	-1.96 (2.79)	-2.62 (3.66)
Q_3 (0.27)	-4.63 (3.20)	-6.86 (4.77)	-7.44* (3.89)	-10.18** (5.11)	-6.83* (3.86)	-9.14* (5.04)	-5.99* (3.45)	-8.37* (4.80)	-2.99 (2.81)	-4.65 (4.34)
Max (2.48)	-0.22 (1.11)	-0.77 (3.40)	-0.19 (3.21)	-0.63 (6.00)	-4.38 (7.41)	-11.96 (12.50)	-5.60 (5.79)	-13.86 (11.09)	-2.82 (3.93)	-9.32 (9.40)

Note. Entries are percentage-point changes in predicted probabilities of no-loss and win outcomes when VAR_i switches from 0 to 1, evaluated at five values of $FinDif_i$ (in €100 m). The sample median is virtually identical to Parity and is therefore omitted.

Table A6. Marginal Probability Effects of VAR by Financial Residual (NF Model)

	2018–19		2019–20		2021–22		2022–23		2023–24	
$FinRes_i$	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win	No-Loss	Win
Min	6.35	12.76	12.12	23.16	41.09**	30.80*	2.10	0.65	5.39	1.41
(-2.10)	(16.08)	(18.02)	(16.02)	(16.62)	(19.21)	(18.63)	(8.02)	(4.14)	(12.79)	(7.46)
Q_1	-0.78	-0.89	-3.51	-3.85	-0.13	-0.15	-1.70	-1.89	0.31	0.36
(-0.26)	(4.23)	(4.81)	(5.20)	(5.59)	(4.32)	(4.93)	(4.69)	(5.19)	(4.03)	(4.61)
Parity	-2.33	-2.98	-6.63*	-8.00*	-4.96	-6.18	-3.77	-4.87	-1.80	-2.48
(0)	(3.13)	(3.98)	(3.67)	(4.29)	(3.38)	(4.08)	(3.25)	(4.09)	(2.90)	(3.93)
Q_3	-3.42	-5.18	-8.92*	-12.41**	-9.15**	-12.47**	-5.55	-7.90	-3.50	-5.50
(0.26)	(3.72)	(5.61)	(4.61)	(6.17)	(4.01)	(5.45)	(3.60)	(5.07)	(3.28)	(5.18)
Max	-0.28	-0.98	-1.12	-3.81	-16.71	-36.64*	-27.96	-20.21	-18.70	-25.14
(2.09)	(7.45)	(10.42)	(15.29)	(17.01)	(19.81)	(20.79)	(19.80)	(18.86)	(16.40)	(17.48)

Note. Entries are percentage-point changes in predicted probabilities of no-loss and win outcomes when VAR_i switches from 0 to 1, evaluated at five benchmark levels of $FinRes_i$ (expressed in € 100 million). The sample median is identical to Parity and is therefore omitted.

Research and Publication Ethics Statement

All stages of this study were conducted in accordance with the research and publication ethics principles of the *Manisa Celal Bayar University Journal of the Institute of Social Sciences*.

Author Contribution Statement

The authors contributed equally to this study.

Conflict of Interest Statement

The authors declare no conflicts of interest with any individual or organization.

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