SOBIE 2026 Proceedings

Society of
Business, Industry, and Economics

26th Annual Academic Conference

Sandestin Golf and Beach Resort
April 8-10, 2026
Destin, Florida

SOBIE 2026

Registration – Bayview Foyer

April 8	April 9	April 10
7:00 – 11:00 AM	7:00 – 11:00 AM	7:00 – 11:00 AM

Wednesday, April 8

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	1- General Business	2- General Business	3- General Business
9:00 – 10:15	4- Marketing	5- AI Topics	6- Student Research
10:30 – 11:45	7- Round Table	8- Finance	9- Student Research
12:00 -1:15	10- Education	11- AI Topics	12- Student Research

Thursday, April 9

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	David L. Black Plenary Breakfast (Bayview Room and Terrace)		
9:00 – 10:15	13- Round Table	14- Student Research	15- Economics
10:30 – 11:45	16- Round Table	17- Student Research	18- Sports
12:00 – 1:15	19- Healthcare	20- Student Research	21- Leadership
1:30 – 2:45	22- AI Topics	23- Student Research	24- International
3:00 – 4:15	25- Cyber	26- Student Research	27- General Business
4:30 – 5:45	28- General Business	29- Open	30- Open

Friday, April 10

	Terrace 1	Terrace 2	Terrace 3
7:30 – 8:45	31- Pedagogy	32- Student Research	33- Accounting
9:00 – 10:15	34- Marketing	35- Student Research	36- Accounting
10:30 – 11:45	37- Finance	38- General Business	39- Student Research
12:00 – 1:15	40-General Business	41- Pedagogy	42- Student Research

SOBIE 2026 Proceedings

Abstracts

Full Papers

AI-Enhanced Early Warning of County Fiscal Distress Using ACFR-Based Financial and Narrative Indicators

Yvonne Ellis[§], Karen McCarron[⸸], Taewoo Park[ϛ], Andrew Stephenson[⸎]

Abstract: Local governments face persistent fiscal pressures arising from revenue volatility, rising service demands, and long-term obligations. Existing early-warning systems used by states and oversight bodies rely primarily on financial ratios derived from Annual Comprehensive Financial Reports (ACFRs), but these indicators are often backward-looking and may fail to detect emerging fiscal stress in a timely manner. This study develops an early-warning fiscal condition prediction framework that integrates traditional financial ratios with narrative characteristics extracted from Management's Discussion and Analysis (MD&A) disclosures. Using Georgia county governments as the empirical setting, models are estimated during the Great Recession period (fiscal years 2006–2012) and evaluated out-of-sample during the COVID-19 pandemic (fiscal years 2020–2022). Fiscal distress is operationalized using a primary measure of persistent operating imbalance and several robust measures capturing alternative dimensions of distress. The study tests whether MD&A textual features, specifically sentiment and readability, provide incremental predictive information beyond financial ratios alone. By validating model performance across two distinct economic shocks, the study assesses the generalizability of narrative-enhanced prediction models. The findings are expected to demonstrate that MD&A disclosures improve the timeliness and accuracy of fiscal distress detection, offering important implications for policymakers, oversight agencies, and stakeholders seeking to enhance fiscal monitoring without imposing additional reporting burdens.

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A Practical First-Step Solution for Implementing HR in Micro Enterprises

Mark Grimes[§], Drew Huey[⸸]

Abstract: Much research has been done on the value that HR adds to organizations, especially in larger organizations. That's great for the really large organizations which have the resources to implement the recommendations that come out of this research. It seems, however, that the amount of research available is directly related to the size of the organization; as organizations get smaller, the amount of research gets less. This really impacts the Micro Enterprises which may desire to implement small-scale HR, but don't know how or where to start. This conceptual paper looks at research across size of organizations, illustrating the lack of material at the Micro-organization level, and suggests what may be the single best HR practice to introduce into these organizations, and how the organization could go about implementing it. As such, this paper offers one option to Micro Enterprises, and opens an avenue for future research looking at organizations which attempt to implement these suggestions.

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Reintroducing Common Sense to Organizations: Identifying Self-imposed Barriers That Impede Managers-in-Training Success Through an Interactive and Experiential Learning Environment

Jamye Long[§], Cooper Johnson[⸸]

Abstract: The value of common sense to organizations would traditionally be considered obvious, or common sense, however that may not be the case. Through studying managers-in-training, particularly their instinctual problem-solving skills of simplistic scenarios, researchers explored the regularity and use of common sense. Researchers sought to better understand the frequency of skills often associated with common sense and quality problem solving, such as critical thinking, communication, brainstorming, researching, and assessing possible solutions. The findings of the study determined that within the construct of the experiment, common sense was a rare commodity. And in a battle of the sexes, common sense was gender neutral.

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Curriculum Adaptation in the Age of AI: An Analysis of Artificial Intelligence Coverage Incorporated into MIS Degree Programs

Fonda Carter[§], Jennifer Pitts[⸸], Robin Snipes[ζ]

Abstract: The technology surrounding artificial intelligence (AI) has undergone rapid evolution, transforming business processes, decision-making systems, and organizational strategies. Business academic programs, especially those in Management Information Systems (MIS), are expected to quickly modify their curricula to incorporate these new and evolving technologies. However, in higher education, there is a lag between the emergence of new technologies and their incorporation into the curriculum. Universities face challenges such as limited faculty expertise, slow curriculum approval processes, and uncertainty regarding appropriate AI competencies for business students. This study examines MIS program requirements and course descriptions provided in the course catalogs of selected universities to investigate the extent to which current MIS degree requirements incorporate artificial intelligence concepts and tools within college curricula.

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From Student Voice to Strategic Action: A Mixed-Methods Gap Analysis of Institutional Priorities at a Regional University

Fonda Carter[§], Jennifer Pitts[ⱡ], Robin Snipes[ζ]

Abstract: As universities face rapid technological changes, shifting demographics, and a more competitive higher education environment, the ability to gather and analyze data directly from students has become crucial for informed strategic planning. Understanding what matters most to students and measuring their satisfaction with how well the institution meets those needs provides university leaders with the evidence needed to make targeted, student-focused decisions. This mixed-methods study builds on previous research at the university level conducted during the institution's strategic planning process. Results from the earlier survey indicated that student priorities and satisfaction levels revealed opportunities for university leadership to address issues that could enhance the student experience and improve key outcomes, such as retention, progression, and graduation rates.

The current research builds on previous findings by concentrating exclusively on students' perceptions of institutional strengths, weaknesses, opportunities, and threats (SWOT) at a regional institution in the southeastern United States. In Phase 1, over 100 undergraduate project management students from six semesters and various delivery modes (online and face-to-face) conducted individual SWOT analyses using mind-mapping techniques. As part of their analysis, students proposed technology-based projects aligned with CSU's strategic plan. A qualitative content analysis of these responses identified common themes within each SWOT category, including affordability and value, faculty accessibility, technology and systems, advising and registration, career services and internships, student engagement, campus safety, and institutional competition. Semester-level trend analysis showed that concerns about institutional competitiveness and technology infrastructure grew over time, whereas affordability remained a consistent and perceived strength. Comparisons between delivery modes revealed notable differences: online students more frequently highlighted gaps in technology, advising shortcomings, and cybersecurity risks, while face-to-face students more often cited issues like campus safety, parking, and student engagement. Collectively, these themes offer a student-driven perspective on essential institutional strengths and areas of concern.

Building on these qualitative findings, Phase 2 will use a quantitative survey administered to a broader cross-section of the CSU student population to validate and expand on the Phase 1 themes centered on the University's strengths and weaknesses. The survey will measure the themes as paired items assessing (1) perceived importance and (2) current satisfaction, enabling a formal gap analysis via an importance-performance framework. This method will rank themes based on the size of the gap between what students consider most important and their satisfaction with the university's current performance in each area. Themes with high importance and low satisfaction will be prioritized for institutional intervention. Gap scores will also be examined across student subgroups, including delivery mode, enrollment status (traditional vs. non-traditional), and military affiliation, to identify whether strategic priorities differ significantly across the student body.

The combined findings from both phases will be shared with university leadership to guide CSU's ongoing strategic planning, accreditation reports, and continuous improvement efforts. By emphasizing the student voice at every stage, from qualitative theme development to

quantitative prioritization, this study demonstrates how structured, problem-based learning activities can incorporate student input into institutional decision-making. Beyond its immediate use at the institution, the two-phase methodology developed here provides a repeatable framework for other universities aiming for a systematic, data-driven approach to student-centered strategic planning. Institutions of different sizes, missions, and student populations can adapt this framework to identify their own student-prioritized issues, assess satisfaction gaps, and allocate resources where they will have the greatest impact. This research adds to the broader literature on strategic planning and importance-performance analysis in higher education while offering a practical model for institutions navigating a rapidly changing landscape.

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Reframing Cyber Policy as Student Success: A Case for Change in Higher Education

Phylicia Taylor[§], Chiquita Brown[⸸], Tejal Mulay[ϛ], DeAnna Burney[⸹], Darryl Scriven[⸎]

Abstract: Universities are increasingly navigating digital harms that extend beyond traditional cybersecurity incidents and directly disrupt student experiences and outcomes. Data breaches, deepfake harassment, doxxing, misinformation, and cyberbullying/harassment can rapidly escalate through social media, creating safety concerns, reputational damage, psychological distress, and academic disruption. Yet institutional responses are often fragmented and distributed across IT, student affairs, legal, counseling, communications, and academic units, resulting in inconsistent support and unclear accountability. This presentation advocates for a student success–centered case for change, arguing that cyber policy should be treated as critical student success infrastructure rather than a narrow compliance or technology function. We present a conceptual framework we hope will spark discussions with participants and aid in decision-making to support universities in developing a pathway forward by mapping key categories of digital harm to pathways of impact on belonging, trust, engagement, persistence and other success outcomes, alongside a practical readiness lens that helps institutions assess their capacity to prevent, respond to, and recover from student-centered digital harms. Because these challenges cut across institutions regardless of size, mission, geography, or resources, the session emphasizes shared shifts universities can make to strengthen coordination, clarify priorities, and build resilient support systems. The session concludes with a student success–centered call to action that reframes digital harms as an institution-wide responsibility and offers a practical way to begin shaping policies and support that match the realities of today's social media environment and the higher education landscape.

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Balancing AI Integration and Learning Integrity: Practical Strategies for the Business Classroom

Phylicia Taylor§, Tejal Mulay⸸, DeAnna Burneyϛ, Keith Quesenberry⸎

Abstract: This interactive roundtable addressed the critical tension between integrating artificial intelligence into the business curriculum and maintaining academic learning integrity. Recent workforce data served as the catalyst for this session, revealing a ninefold increase in businesses outside of the technology sector seeking employees with AI capabilities. Panelists argued that career success now depends on a student's ability to apply AI tools while exercising human judgment, critical thinking, and discipline expertise. However, the session acknowledged the challenge that the same tools intended to prepare students for careers could be misused to circumvent the learning process.

The session offered practical strategies for integrating AI in ways that enhanced rather than replaced learning. Dr. Phylicia Taylor focused on moving beyond technical skills to teach digital responsibility, emphasizing how Gen Z must learn to judge, justify, and govern AI use within ethical and professional frameworks. Dr. Amy Schumacher-Rutherford demonstrated how generative AI tools were utilized to create interactive classroom environments and hands-on activities that encouraged deeper content engagement while curbing misuse.

Technical applications were further explored by Dr. Kelli S. Burns, who detailed the integration of AI into research methods through synthetic audience personas, AI-driven social listening, and qualitative analysis assistant tools. Finally, Keith Quesenberry demonstrated the use of Custom GPTs as a solution to limit misuse. These tools were designed to act as Socratic tutors, prompting students with clarifying questions to guide them through complex topics, such as market segmentation and brand positioning, without completing the assignments for them. The session concluded with a collaborative discussion and the sharing of resources for AI-enhanced assignment design.

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Global Turbulence and Sustainability in Emerging Markets

Alper Gormus[§], Elif Gormus[⸸]

Abstract

We analyze how global risks and sustainability interact in emerging equity markets by estimating a daily time-varying parameter VAR (TVP-VAR) and computing generalized forecast-error variance decompositions to obtain dynamic connectedness measures. We construct two portfolios of emerging-market equity funds based on Morningstar high and low sustainability ratings and embed them in an eight-variable global network with Brent, the U.S. dollar index, VIX, S&P 500, gold, and EM volatility. We then overlay geopolitical risk (GPR), economic policy uncertainty (GEPU), and the Global Supply Chain Pressure Index (GSCPI) on network metrics. The Total Connectedness Index (TCI) is high on average and surges during global crisis periods. Supply-chain stress is positively associated with system-wide connectedness, while GEPU reduces the LOW portfolio's net outward spillovers; episodically, GPR elevates the HIGH portfolio's net influence. The equity–volatility block serves as the principal transmitter toward EM risk, the dollar, and commodities, whereas USD and Brent act as receivers. These results clarify how turbulence propagates to emerging markets and how sustainability segmentation shapes transmission channels, offering actionable guidance for asset allocation, hedging, and policy surveillance.

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Introduction

Geopolitical shocks and policy uncertainty increasingly shape global capital flows, yet their transmission to emerging markets depends critically on balance-sheet constraints, currency channels, and the composition of investable assets. A large literature shows that volatility and dollar conditions govern risk propagation (Bruno & Shin, 2023; Johnson, 2017), while oil demand–supply mix and commodity bottlenecks interfere with equity pricing (Ready, 2018). This emphasis on dollar conditions is consistent with policy-oriented evidence that strong-dollar episodes transmit broadly through trade, funding, and global financial conditions (Dollar & Sheets, 2020). In parallel, sustainability affects cash-flow resilience and investor clientele: firms with strong ESG/CSR perform better in crises (Lins, Servaes, & Tamayo, 2017) and investors demonstrably value sustainability attributes in equilibrium (Hartzmark & Sussman, 2019; Pástor, Stambaugh, & Taylor, 2021, 2022; Pedersen, Fitzgibbons, & Pomorski, 2021). Despite these advances, we know less about how sustainability segmentation interacts with geopolitical risk in the networked setting that characterizes emerging markets. Recent evidence indicates that geopolitical risk and pandemic episodes reshape connectedness across markets (Wang, et al. 2022) and that green assets exhibit nontrivial connectivity under geopolitical risk and market-implied volatility (Bajra & Aliu, 2025). We build on this foundation by studying sustainability-sorted emerging-market portfolios inside a global network and by directly mapping geopolitical risk and supply-chain pressure to system-wide and directional connectedness.

Our contribution is threefold. First, we provide high-frequency evidence on how geopolitical turbulence interacts with sustainability to rewire cross-market transmission. Using a daily TVP-VAR with generalized FEVDs, we show that the Total Connectedness Index (TCI) is elevated on average and increases sharply during well-identified episodes—China 2015, Brexit 2016, "Volmageddon" 2018, COVID-19 2020, Russia–Ukraine 2022, and April 2025 U.S. tariff announcement—highlighting that shocks first tighten risk-bearing capacity and funding channels before arriving in emerging assets (Bruno & Shin, 2023; Johnson, 2017). Second, we document an ESG asymmetry: the LOW portfolio is a stronger net transmitter in tranquil periods, whereas the HIGH portfolio retains influence when geopolitical risk surges, aligning with theories in which sustainability hedges salient risks and attracts stable clientele (Lins et al., 2017; Hartzmark & Sussman, 2019; Pástor et al., 2021, 2022; Pedersen et al., 2021). Third, we relate connectedness to macro-turbulence. Supply-chain stress (GSCPI) is positively associated with TCI, while GEPU reduces the LOW portfolio's transmitter role and GPR episodically elevates the HIGH portfolio's net influence. These patterns are consistent with evidence that geopolitical risk materially affects emerging markets (Kannadhasan & Das, 2020) and that connectedness intensifies during pandemic and conflict episodes (Wang et al., 2022). Overall, the paper further explores how geopolitical risk and sustainability co-determine the origin and landing points of shocks in emerging markets, offering new measurements and interpretations for investors and policymakers.

Methodology

We model the joint dynamics of the variables with a TVP-VAR that allows autoregressive coefficients to evolve over time. The observation equation links current outcomes to their lagged values, while the state equation governs the law of motion of the time-varying parameters. The estimator updates the parameters with Kalman/recursive least squares under forgetting factors, which captures gradual structural change without imposing arbitrary rolling windows (Koop & Korobilis, 2014).

$$
\begin{aligned}
y_t &= \beta_t z_{t-1} + \varepsilon_t, \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \\
\mathrm{vec}(\beta_t) &= \mathrm{vec}(\beta_{t-1}) + v_t, v_t \mid \Omega_{t-1} \sim N(0, \mathrm{T}_t) \\
z_{t-1} &= \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \cdots \\ y_{t-p} \end{pmatrix}, \beta_t = \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \\ \cdots \\ \beta_{pt} \end{pmatrix}
\end{aligned} \tag{1}
$$

At each date, we compute generalized H-step-ahead FEVDs to quantify how much of each variable's forecast error variance is explained by shocks to every other variable. The 'generalized' implementation makes the decomposition invariant to variable ordering, which is desirable in multi-asset settings (Diebold & Yilmaz, 2012).

$$
C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{n} V_{ij,t}(H)}{\sum_{i,j=1}^{n} V_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{n} V_{ij,t}(H)}{n} * 100 \tag{2}
$$

The Total Connectedness Index (TCI) measures, at each point in time, the share of the system's forecast variance that is attributed to cross-series transmission (i.e., off-diagonal contributions in the GFEVD). Higher TCI values indicate tighter coupling of the system through shock propagation channels (Antonakakis & Gabauer, 2017; Diebold & Yilmaz, 2012).

We summarize outgoing and incoming spillovers using directional connectedness measures. For variable i, the 'TO' measure aggregates the fraction of other variables' forecast variances attributable to shocks to i (risk transmitted to the network), while the 'FROM' measure aggregates the fraction of i's variance explained by shocks to others (risk received from the network). These are computed directly from the columns and rows of the time-varying GFEVD matrix (Antonakakis & Gabauer, 2017).

$$
C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} V_{ji,t}(H)}{\sum_{j=1}^{n} V_{ji,t}(H)} * 100 \tag{3}
$$

$$
C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{n} V_{ij,t}(H)}{\sum_{i=1}^{n} V_{ij,t}(H)} * 100 \tag{4}
$$

Net connectedness for variable i is the difference between its outward and inward spillovers, Net NPDC = FROM - TO; positive values indicate net transmitters, negative values indicate net receivers. For bilateral analysis, net pairwise directional connectedness (NPDC) contrasts the contribution from j to i with the contribution from i to j, thereby isolating 'who moves whom' in the network (Antonakakis & Gabauer, 2017).

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{5}$$

$$NPDC_{ij}(H) = \left(V_{ji,t}(H) - V_{ij,t}(H)\right) * 100 \tag{6}$$

We estimate the TVP-VAR on daily data to reflect high-frequency evolution in propagation and cross-market shock co-movement. At each date, we form the generalized FEVD at a finite horizon H and compute TCI, TO, FROM, NET, and NPDC. Because the connectedness metrics are generalized, they do not depend on variable ordering. For comparability with lower-frequency macro-turbulence indicators (e.g., GPR, GEPU, GSCPI), we aggregate the daily measures to monthly averages solely for overlay and regression analysis. The connectedness itself is always derived from the daily TVP-VAR (Antonakakis & Gabauer, 2017; Diebold & Yilmaz, 2012; Koop & Korobilis, 2014).

Data

We assemble a balanced daily panel from Morningstar, spanning 06/05/2015–06/30/2025, and supplement it with monthly global turbulence indices. The eight daily variables are Brent crude (Brent), S&P 500 (SP500), Cboe VIX (VIX), gold (Gold), the nominal broad U.S. dollar index (USD), the Cboe Emerging Markets Volatility Index (VXEEM), and two sustainability-sorted EM fund portfolios (HIGH, LOW).

HIGH and LOW are capitalization-weighted portfolios of U.S.-domiciled, USD-priced EM equity funds, classified by Morningstar's sustainability ratings. In order to draw a contrast, only funds in the High and Low categories are included, with weights proportional to total net assets (TNA) and updated when Morningstar refreshes holdings. This yields investable daily proxies for high- and low-sustainability EM exposure.

Monthly overlays use Caldara and Iacoviello's GPR (2022), Baker–Bloom–Davis GEPU (2016), and the NY Fed's GSCPI (Benigno et al., 2022). Daily connectedness is aggregated to monthly averages and matched to these indices. Daily series enter the TVP-VAR in standardized levels; descriptive statistics on log returns and monthly turbulence levels are reported separately.

Table 1: Descriptive Statistics

Panel A

Series	Mean	Std	Min	Median	Max	Skew	Kurt	JB	ADF
HIGH	0.012	1.114	-9.091	0.064	6.191	-0.481	4.890	0.000	0.000
LOW	0.024	0.968	-10.689	0.093	6.175	-1.609	15.576	0.000	0.000
SP500	0.048	1.162	-12.762	0.074	9.090	-0.652	15.539	0.000	0.000
VIX	0.006	8.165	-44.245	-0.730	76.825	1.300	7.947	0.000	0.000
USD	0.004	0.356	-2.088	0.000	2.488	0.095	4.902	0.000	0.000
Brent	0.002	2.413	-26.825	0.155	19.080	-0.829	14.071	0.000	0.000
VXEEM	-0.011	8.599	-101.357	-0.524	97.617	0.031	22.355	0.000	0.000
Gold	0.041	0.946	-5.056	0.044	5.601	-0.146	3.514	0.000	0.000

Panel B

Series	Mean	Std	Min	Median	Max	Skew	Kurt
GPR	110.216	36.550	58.420	104.270	318.950	2.187	8.694
GEPU	226.668	81.912	106.324	211.096	629.943	1.763	5.393
GSCPI	0.601	1.347	-1.570	0.140	4.450	1.119	0.428

Notes: Panel A reports daily log returns for eight series: HIGH and LOW are emerging-market equity portfolios formed by Morningstar sustainability ratings; SP500 = S&P 500; VIX = Cboe VIX; USD = nominal broad U.S. dollar index; Brent = Brent crude oil; VXEEM = EM equity volatility index. Skew and Kurt denote sample skewness and excess kurtosis. JB is the Jarque–Bera normality test p-value. ADF is the Augmented Dickey–Fuller unit-root test p-value with intercept and AIC-selected lag. Panel B reports monthly levels of GPR, GEPU, and GSCPI; therefore JB and ADF are not included in Panel B by design. We intentionally keep Panel B focused on level-distribution characteristics to preserve their interpretation as turbulence proxies.

Panel A (Table 1) exhibits hallmark features of high-frequency returns: medians near zero, substantial dispersion for SP500 and VIX, comparatively lower volatility for USD and Gold, and pronounced leptokurtosis. Augmented Dickey–Fuller p-values reject unit root, supporting stationarity of daily returns. Panel B shows right-skewed distributions for GPR and GEPU and the greatest variability for GSCPI, consistent with episodic supply-chain bottlenecks. These properties align with this study's connectedness evidence, in which heavy-tailed innovations and volatile macro-turbulence coincide with elevated, time-varying TCI and state-dependent ESG spillovers.We estimate the TVP-VAR on daily data to reflect high-frequency evolution in propagation and cross-market shock co-movement. At each date, we form the generalized FEVD at a finite horizon H and compute TCI, TO, FROM, NET, and NPDC. Because the connectedness metrics are generalized, they do not depend on variable ordering. For comparability with lower-frequency macro-turbulence indicators (e.g., GPR, GEPU, GSCPI), we aggregate the daily measures to monthly averages solely for overlay and regression analysis. The connectedness itself is always derived from the daily TVP-VAR (Antonakakis & Gabauer, 2017; Diebold & Yilmaz, 2012; Koop & Korobilis, 2014).

Results

The daily TVP-VAR with generalized FEVD reveals a highly connected EM–global system whose intensity fluctuates with macro-geopolitical regimes. Total connectedness is elevated on average and rises sharply during six canonical turbulence episodes: China's equity/FX turmoil in 2015 (August–October), the Brexit referendum in June 2016, the February 2018 "Volmageddon," the COVID-19 collapse and rebound in 2020 (February–April), the Russia–Ukraine invasion in early 2022, and the April 2025 U.S. tariff announcement. Figure 1 displays the daily TCI with shading for these windows, highlighting the COVID-19 crash as the most abrupt surge. Spikes in TCI align closely with well-recognized turbulence episodes, reflecting regimes in which shocks transmit through intermediary balance sheets and risk-bearing channels before arriving in emerging markets (He et al. 2017; Adrian et al. 2019). These dynamics are consistent with the broader view that global turbulence compresses risk-bearing capacity and amplifies nonlinear propagation of shocks (Adrian et al., 2019), thereby raising the share of forecast variance explained by cross-market disturbances and increasing system-wide connectedness.

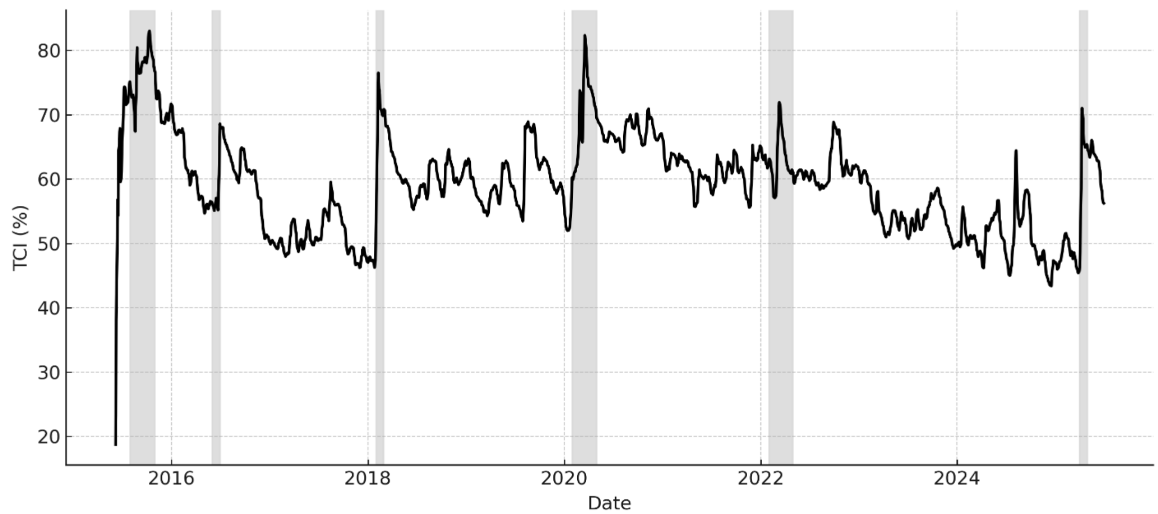

Figure 1. Daily TCI with six crisis windows shaded

Notes: Shaded windows—2015-08 to 2015-10 (China equity/FX); 2016-06 (Brexit); 2018-02 (Volmageddon); 2020-02 to 2020-04 (COVID-19); 2022-02 to 2022-04 (Russia–Ukraine); 2025-04 (U.S. Tariff announcement).

The cross-sectional structure of spillovers is also economically intuitive (Table 2). Averaging the daily connectedness measures over the sample, the S&P 500 is the dominant net transmitter, followed by the low-sustainability portfolio (LOW) and the VIX, while Brent, the U.S. dollar index, EM volatility (VXEEM), and Gold are net receivers. These roles imply an equity–volatility block that exports risk broadly into commodities, the dollar, and EM risk, with ESG portfolios positioned between global and EM nodes. The asymmetry between ESG strata—LOW being more of a transmitter than HIGH in normal times—suggests that lower-sustainability holdings are more systematically implicated in the propagation of shocks, whereas high-sustainability holdings are relatively less central transmitters. This finding is consistent with evidence that stronger CSR/ESG preserves trust and investor clientele and mitigates downside exposures in crises (Lins et al. 2017; Hartzmark & Sussman, 2019), and with equilibrium models in which preferences for sustainability generate distinct cyclicality and hedging properties for 'green' assets (Pástor et al. 2021; Pástor et al. 2022; Pedersen et al. 2021).

Table 2. TCI Network - Directional Results

	FROM	TO	NET
SP500	62.61	92.93	30.32
LOW	68.41	83.52	15.1
VIX	67.29	76.94	9.65
HIGH	69.44	76.83	7.39
Gold	39.63	30.23	-9.4
VXEEM	68.41	51.94	-16.47
USD	56.98	39.48	-17.49
BRENT	41.62	22.53	-19.1

Pairwise net spillovers (Table 3) pinpoint the strongest channels—most notably S&P 500↔Brent, S&P 500↔U.S. dollar, and VIX↔VXEEM—consistent with equity-to-commodity and equity-to-FX risk-taking and funding mechanisms (He et al. 2017; Adrian et al. 2019).

Table 3. Top net pairwise directional connectedness (NPDC) links.

FROM	TO	NPDC
SP500	BRENT	7.49
SP500	USD	7.41
VIX	VXEEM	7.08
SP500	VXEEM	6.78
SP500	Gold	5.81

Next, we evaluate whether macro-turbulence indicators line up with movements in ESG spillovers by overlaying standardized monthly Net(LOW) and Net(HIGH) with standardized geopolitical risk (GPR), economic policy uncertainty (GEPU), and the Global Supply Chain Pressure Index (GSCPI). As presented in Figure 2, outside acute turmoil, Net(LOW) typically exceeds Net(HIGH). When GPR surges or supply-chain stress intensifies, however, the gap narrows or reverses, suggesting that turbulence reallocates risk-bearing capacity across ESG tiers. Because we construct the overlay by aggregating daily connectedness to the monthly frequency, it directly reflects movements in network centrality rather than simple price co-movements, thereby isolating changes in transmission roles.

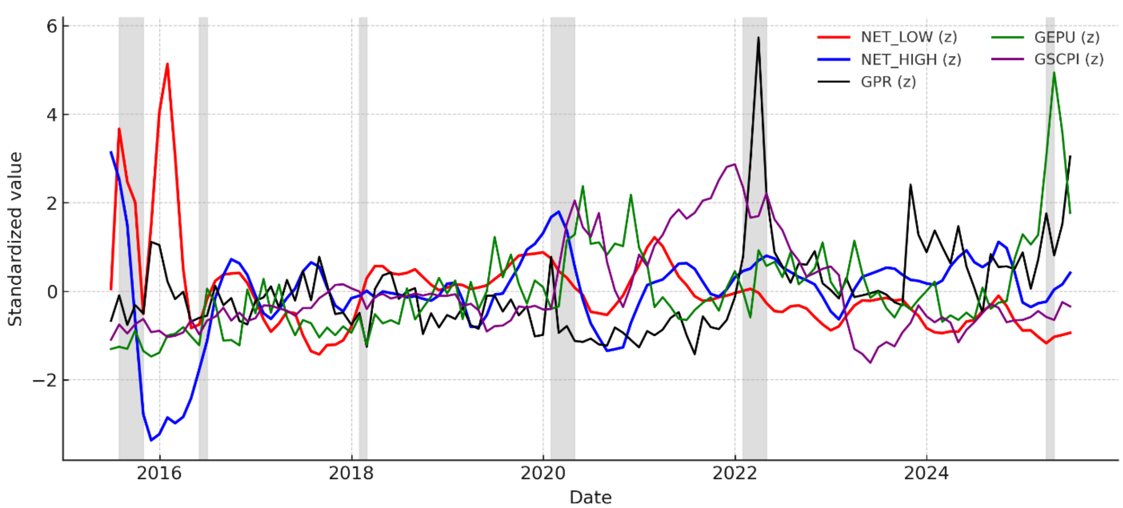

Figure 2. Monthly Net(LOW/HIGH) with GPR, GEPU and GSCPI (standardized)

Notes: Shaded windows—2015-08 to 2015-10 (China equity/FX); 2016-06 (Brexit); 2018-02 (Volmageddon); 2020-02 to 2020-04 (COVID-19); 2022-02 to 2022-04 (Russia–Ukraine); 2025-04 (U.S. Tariff announcement).

Further analyzing the interactions, monthly overlays corroborate a turbulence–tightening nexus (Table 4). Geopolitical risk and global economic policy uncertainty are associated with higher total connectedness, while elevated supply-chain pressure coincides with tighter networks. This interpretation is consistent with evidence that pandemic-era supply disruptions materially constrained production and amplified bottleneck-driven uncertainty, providing a real-economy channel that can intensify cross-market transmission (Moutray, 2020). At the sustainability margin, HIGH's relative influence rises with geopolitical risk, whereas LOW's dominance is a feature of tranquil regimes. These patterns accord with evidence on risk-taking cycles, dollar strength, and the valuation of sustainability (Lins et al. 2017; Hartzmark & Sussman, 2019; Pástor et al. 2021, 2022; Pedersen et al. 2021; Ready, 2018; Bruno & Shin, 2023).

Table 4. Influence of GPR, GEPU, and GSCPI on Network Connectedness (Standardized Betas; HAC-robust)

Panel A: System-wide connectedness (TCI) and per-variable NET (send–receive balance).

	TCI	HIGH	LOW	SP500	VIX	USD	BRENT	VXEEM	GOLD
GPR	-0.15	0.13*	-0.06	0.10	-0.09	0.11	0.18	-0.28**	-0.05
GEPU	0.03	0.05	-0.23*	-0.29	0.48***	0.19	0.08	0.11	-0.06
GSCPI	0.27**	0.10	-0.04	-0.11	0.38***	-0.02	0.10	-0.12	-0.10

Panel B: Spillovers sent to others

TO =>	HIGH	LOW	SP500	VIX	USD	BRENT	VXEEM	GOLD
GPR	0.13	-0.12	0.08	-0.10	0.10	-0.19*	-0.32**	0.01
GEPU	0.09	-0.10	-0.23	0.48***	0.06	0.23**	0.07	-0.14
GSCPI	0.17*	0.11*	-0.04	0.45***	0.17	0.26**	-0.05	-0.16*

Panel C: Spillovers received from others

FROM =>	HIGH	LOW	SP500	VIX	USD	BRENT	VXEEM	GOLD
GPR	-0.03	-0.11	-0.13*	0.03	-0.04	-0.30**	-0.06	0.16
GEPU	0.10	0.38**	0.36***	-0.26	-0.19	0.09	-0.08	-0.20*
GSCPI	0.16	0.36***	0.32***	0.02	0.22**	0.10	0.18	-0.15

Notes: Entries are standardized regression coefficients from monthly OLS of each connectedness metric on standardized GPR, GEPU, and GSCPI with HAC(3) standard errors. Asterisks denote significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. TCI is the monthly average of the daily Total Connectedness Index. TO and FROM are monthly averages of daily generalized FEVD-based directional connectedness.

These results carry distinct implications for emerging-market risk transmission. The equity–volatility block (S&P 500 and VIX) is the main source of shocks, transmitting to commodities, the dollar, and EM risk—consistent with variance-risk premia and intermediary constraints (Johnson, 2017; He et al., 2017; Adrian et al., 2019). Under turbulence, the network tightens, particularly when supply-chain pressures rise; significant GSCPI effects confirm that real frictions amplify cross-market transmission (Bruno & Shin, 2023). Sustainability asymmetry is also meaningful: LOW transmits more in tranquil periods but weakens under policy uncertainty, while HIGH retains or gains centrality with heightened geopolitical risk, consistent with models of sustainability preferences (Pástor et al., 2021, 2022) and portfolio evidence on ESG tilts (Pedersen et al., 2021). Gold mostly absorbs shocks, with only episodic transmission, underscoring its tactical rather than universal safe-haven role (Ready, 2018).

Overall, shocks arise in developed-market equity/volatility, flow into the dollar and commodities, and then into EM risk, with ESG portfolios mediating these channels. Turbulence—geopolitical risk, policy uncertainty, or supply-chain stress—raises connectedness and shifts transmitter–receiver roles in ways aligned with recent finance research. The TVP-VAR captures these dynamics across frequencies, showing where shocks originate, propagate, and settle.

Conclusion

The evidence indicates that turbulence transmits to emerging markets primarily through the developed-market equity–volatility complex and the dollar–commodity channel, with sustainability shaping the allocation of influence along the way. On average, S&P 500 and VIX shocks radiate outward, while USD and Brent absorb shocks, and EM volatility (VXEEM) amplifies transmissions once disturbances reach the periphery. Sustainability-based segmentation also plays an important role in risk transmission. The LOW portfolio acts as a stronger transmitter in calm conditions, but its outward role diminishes when policy uncertainty rises, while the HIGH portfolio's influence persists or increases when geopolitical risk intensifies. At the system level, supply-chain stress associates positively with TCI, consistent with a mechanism in which real bottlenecks and disruption-driven uncertainty strengthen cross-market spillovers (Moutray, 2020; Bruno & Shin, 2023; Ready, 2018).

These results are significant for both portfolio construction and policy surveillance. Investors can tilt hedges and liquidity buffers toward periods when the network tightens and transmission turns outward from the equity–volatility block; risk committees can calibrate limits around episodes of elevated geopolitical risk and supply-chain stress. For policymakers and central banks, the findings provide a real-time barometer of EM vulnerability to global shocks, linking classic risk-taking channels and dollar conditions to the valuation of sustainability (Bruno & Shin, 2023; Ready, 2018; Lins et al., 2017; Hartzmark & Sussman, 2019; Pástor et al., 2021, 2022; Pedersen et al., 2021).

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Fiscal Policy and Business Cycles Synchronization Across U.S. States

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Introduction

This paper investigates whether business cycle synchronization across U.S. states is related to differences in fiscal policy across states. More precisely, do states with differing fiscal positions show more or less business co-movement than do otherwise similar states? Although U.S. states are subject to common national shocks and a unified monetary policy, their economic fluctuations often differ substantially, raising important questions about the sources of these differences.

In the United States, state governments operate under balanced budget requirements, but these rules vary in their stringency and enforcement across states. As a result, states retain differing degrees of fiscal flexibility, allowing for variation in government spending and fiscal responses over the business cycle. These institutional differences can lead to cross-state variation in government spending and fiscal policy.

This paper examines whether cross-state differences in fiscal policy—measured by government spending as a share of state GDP—are associated with differences in business cycle synchronization.

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Literature Review

A large literature examines the determinants of business cycle synchronization across regions, emphasizing factors such as trade integration, industrial structure, and financial linkages. However, relatively less attention has been given to the role of fiscal policy within a country.

Darvas et al. (2007) study the impact of fiscal divergence between regions on the synchronization of the business cycle between these regions. They examine 21 OECD countries and find that fiscal convergence between two countries leads to more synchronized business cycles.

Following Darvas et al. (2007), Lan and Sylwester (2010) shows that regions with more similar fiscal positions tend to have more synchronized business cycles in China.

This paper applies this framework to U.S. states.

Methodology

3.1 Data

We use annual data for all 50 U.S. states over the period 20010–2019. State-level economic activity is measured using the state coincident index constructed by the Federal Reserve Bank of Philadelphia. To align with fiscal data, the index is converted to annual growth rates.

Data on state government spending are obtained from the U.S. Census Annual Survey of State Government Finances, while state GDP data are sourced from the Bureau of Economic Analysis. Government spending is expressed as a share of state GDP to provide a comparable measure of fiscal policy across states.

3.2 Econometric Specification

The empirical analysis relies on two key variables: fiscal divergence and correlations of business cycles. We discuss each in turn.

Following Darvas et al. [2005], we measure fiscal divergence between state i and state j during sub-period τ as differences in budgetary positions of the two states:

$$FiscalDiverge_{ij\tau} \equiv 1/\tau * \sum\left(\left|Budg_{it} - Budg_{jt}\right|\right) \quad (1)$$

where $Budg_{it}$ is the state nominal government budget surplus of state i at time t, measured as a percentage of nominal GSP. $FiscalDiverge_{ij\tau}$ denotes the average (over sub-period τ) absolute difference in the government budget position between state i and state j. A larger value of $FiscalDiverge_{ij\tau}$ means a higher average divergence between the fiscal positions of the two states.

The second key variable captures the degree of business cycle synchronization between provinces i and j. We use the annual growth rates of state coincident index.

Our simplest empirical specification follows that of Frankel and Rose [1998] and also used by Darvas et al. [2007]. Frankel and Rose [1998] focus on business cycle synchronization with respect to trade. The benchmark regression takes this simple form:

$$corr_{ij\tau} = \alpha_{\tau} + \beta\ FiscalDiverge_{ij\tau} + \varepsilon_{ij\tau} \qquad (2)$$

$corr_{ij\tau}$ denotes the correlation coefficient between state i and state j over sub-period τ .

We follow Winters (2009) closely, who estimates individual wage equations and then regresses regional fixed effects on housing prices and amenities. Due to data limitations, we do not have access to individual-level microdata. Instead, we use provincial-level average wages, average housing prices, and a composite quality of life index to estimate wage regressions directly at the aggregate level.

Literature Review

From table 1, the coefficient on fiscal policy differences is negative and statistically significant.

This suggests that greater differences in fiscal policy across states are associated with lower levels of business cycle synchronization.

Although statistically significant, the magnitude is relatively small, indicating that fiscal policy differences play a limited role compared to broader national factors such as federal fiscal policy and monetary policy.

Table 1. Fiscal Policy Differences and Business Cycle Synchronization

Variables	Baseline
Fiscal Difference	−0.01396*
	(0.0055)
Observations	1,225
R-squared	0.018

Notes: Standard errors are in parentheses. Coefficients significantly different from zero at 0.05 and0.01 level marked with one and three asterisk(s)

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The Effects of Stoppage Time Rule Changes on Actual and Market-Based Expected Scoring in Top-Flight Soccer

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Abstract

Significant stoppage time rule changes were introduced during the 2022 FIFA World Cup, altering match duration in professional soccer. This study examines the impact of these changes on actual and market-expected scoring across major European leagues during the 2022-23 season. Utilizing a natural experiment framework comparing pre- and post-World Cup match data, we find that while rule changes increased stoppage-time goals, overall goals per match declined. Furthermore, betting the "over" in the totals market resulted in statistically significant losses post-World Cup, likely driven by an influx of recreational or "square" bettors.

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Introduction and Motivation

Prior to the 2022 FIFA World Cup, FIFA Referees Committee Chairman Pierluigi Collina announced a shift in stoppage time calculation to address matches featuring fewer than 50 minutes of actual playing time.

(Inside FIFA 2022) This implementation resulted in a significant increase in game duration; for instance, France-Australia saw over 67 minutes of active play. (Inside FIFA 2022). The 2022 World Cup saw 172 goals scored, making it the highest scoring World Cup in history. (Associated Press 2022) As these protocols were adopted by top-flight leagues mid-season, the 2022-23 period provides a unique dataset to observe effects on scoring and betting market efficiency.

We hypothesized that the increase in game duration would lead to an increase in scoring, and then potentially to profitability on betting the over in post-World Cup matches.

Data and Summary Statistics

The study analyzed 3,525 matches across eleven major leagues. These are the "main leagues" listed on Football-Data.co.uk, and include the top-flight leagues from England, Scotland, Germany, Italy, Spain, France, Netherlands, Belgium, Portugal, Turkey, and Greece. Note that there were 3,554 scheduled matches, but an earthquake in Turkey resulted in 29 matches being cancelled, resulting in 3,525 matches available for analysis during the 2022-23 season.

Table 1 provides summary statistics for the 2022-23 season as a whole, and the values for matches played pre-World Cup and post-World Cup.

Table 1: Summary Statistics

	Season		**Pre-WC**		**Post-WC**	
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Goals per match	2.7989	1.6943	2.8406	1.7346	2.7704	1.6660
Home team goals	1.5710	1.3490	1.5776	1.3784	1.5666	1.3290
Away team goals	1.2278	1.1726	1.2629	1.2080	1.2038	1.1476
Over closing odds	1.8950	0.3642	1.8582	0.3244	1.9200	0.3872
Betting the over profits	-0.0305	0.9467	-0.0084	0.9334	-0.0455	0.9556
Number of observations	3,525		1,430		2,095	

The tables below detail the scoring distribution for five of these leagues across different match periods.

Table 2: Scoring Breakdown 2022/23 Full Season (Average Goals)

League	1st Half (1'-45')	1st Half Stop (45'+)	2nd Half (46'-90')	2nd Half Stop (90'+)
Bundesliga	1.26	0.10	1.48	0.33
Premier League	1.16	0.07	1.40	0.22
Ligue 1	1.13	0.08	1.31	0.30
Serie A	1.03	0.07	1.21	0.25
La Liga	1.00	0.08	1.13	0.30

Table 3: Scoring Breakdown of Stoppage Time Pre-WC vs. Post-WC (Average Goals)

League	Pre-WC 90'+Goals	Post-WC 90'+ Goals	Change
Bundesliga	0.28	0.37	+0.09
Premier League	0.18	0.26	+0.08
Ligue 1	0.27	0.31	+0.04
Serie A	0.23	0.26	+0.03
La Liga	0.30	0.30	0

While scoring in the final minutes increased in most leagues, contrary to expectations, the overall goal average per match trended downward due to decreased scoring in regulation time.

Empirical Analysis and Profitability

We analyzed the "Over 2.5" goals market using decimal odds. The summary statistics for the full season and the period comparisons reveal a shift in market efficiency.

Table 4 illustrates how this totals market works, and translates the decimal odds into American odds and implied probabilities using an example from a game between Arsenal Football Club of London, England and Sporting Club of Lisbon, Portugal:

Table 4: Decimal Odds in Soccer Totals Markets

Line	Decimal Odds	American Odds	Implied Probability
Over 2.5	1.89	-112	52.91%
Under 2.5	1.88	-114	53.19%

This means that in order to be profitable at these odds, an over bet would have to cover more than 52.91% of the time. We examined the change in profitability of betting the over in the top soccer leagues before and after the World Cup. The results are shown below in Table 5.

Table 5: Change in Profits (Pre-WC vs. Post-WC)

Period	Variable	Obs	Mean	Std. Dev.
Pre-WC	profit_over	1,430	-0.0084	0.9333
	Scoreline	1,430	2.8405	1.7346
Post-WC	profit_over	2,095	-0.0454	0.9556
	Scoreline	2,095	2.7704	1.6660

The mean profit for betting the "over", again contrary to expectations, dropped from -0.0084 pre-WC to -0.0454 post-WC. This is a substantial decline, meaning that that the bets were five times less profitable after the world cup. Further, as illustrated in Table 6, we find this decline in profitability to be statistically significant.

Table 6: Decline in Profitability of Over after World Cup

Variable	Obs	Mean	Std. Error	t-statistic	p-value (Pr<-.008)
profit_over	2,095	-.0454316	.020877	-1.7729	0.0363

This decline is further highlighted in the t-test results for specific game weeks post-tournament, as shown in Table 7.

Table 7: One-Sample T-Tests for profit_over (Post-WC)

Gameweek	Obs	Mean	t-stat	Pr(T<t)
Week < 20	83	0.0002	0.0025	0.5010
Week 20	73	-0.1628	-1.4721	0.0727
Week 21	79	-0.1478	-1.3044	0.0980

Discussion and Conclusion

The 2022 stoppage time rule changes successfully increased match duration and stoppage-time goals. However, the 2022-23 season ultimately saw lower total scoring and significant financial losses for "over" bettors. There are a number of potential reasons for this unexpected result, starting with changes to the composition of the market itself.

The World Cup and its immediate aftermath saw a surge in recreational "square" bettors caters to such bettors). These bettors typically favor "over" outcomes, potentially inflating the value of the over bets. Further, as noted earlier, the 2022 World Cup was the highest scoring in history, which may have caused such casual bettors to overstate the amount of scoring they should expect.

The increase in recreational betting activity on soccer was observed domestically and globally. In the US, American Gaming Association (AGA) estimated that 20.5 million American adults (8% of the population) planned to wager a total of $1.8 billion on the tournament. (AGA 2022)Flutter Entertainment (owner of FanDuel) recorded a peak of 12.1 million Average Monthly Players (AMPs) in Q4 2022 (the World Cup quarter), which remained elevated into the Q1 2023 Premier League and Bundesliga schedule. (Porter 2024)

Abroad, the story was similar. In France, 177,000 new accounts were created on licensed platforms during the competition. French betting turnover was significantly higher at €615 million on the 2022 World Cup compared to the €366 million wagered during the 2018 World Cup.(ANJ 2023) In the United Kingdom (where our data source, bet365, is based) Entain (owner of Ladbrokes and Coral) reported a 15% increase in active customers during the 2022 World Cup. (Fontaine 2026)

Thus, we see a clear trend of new casual bettors being attracted to soccer as a result of the rare mid-season World Cup and affecting the markets. There are also other factors not directly related to market participants that could have contributed to the scoring decline.

One such contributing factor was deteriorating physical and mental health of players due to the increased amount of matches caused by the in-season World Cup. Reports indicate that 44% of players experienced increased physical fatigue and 23% reported mental fatigue in the months following the tournament. (Football Benchmark 2023) Fatigue often results in slower match tempos and less clinical finishing. Additionally, a major study found that injury severity in Europe's top leagues increased significantly post-tournament. Players were sidelined for an average of 8 days longer in the second half of the season, with hamstring injuries increasing by 130% and ankle injuries by 170%. (Howden 2023) The loss of high-impact attacking players directly lowers the probability of "Over 2.5" goal results.

Beyond injuries, there were tactical changes that likely restrained scoring. After a major mid-season disruption, many club managers prioritize defensive stability to "stop the bleed" and secure points. This is particularly true for away teams, who saw their scoring drop by nearly 5%. Further, with matches scheduled every few days to make up for the World Cup break, teams often "managed" games once they had a lead rather than pushing for a high-scoring blowout. This creates a high frequency of 1-0 or 2-0 results, which naturally favors totals under 2.5.

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Common Value Auctions in the Classroom: A Computational Approach using the Wallet Game

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Abstract

Teaching Common Value Auctions (CVAs) and the Winner's Curse presents a unique pedagogical challenge due to the mathematical conditioning required for equilibrium bidding. This article proposes a teaching methodology centered on the "Wallet Game," which provides analytical tractability and economic intuition. We derive symmetric Nash equilibria for both Second-Price and First-Price auctions using both pivotal conditioning and direct expected payoff maximization. The contribution of the article is to use Monte Carlo simulations as a pedagogical tool to show students the mechanics of the Winner's Curse and why naive bidding generates lower profits. We provide code compatible with MATLAB and open source GNU Octave to allow educators to empirically verify these theoretical results in the classroom.

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Introduction and Literature Review

Common Value Auctions (CVAs) are a foundational topic in advanced microeconomics, game theory, and industrial organization. Unlike private value auctions, where a bidder's valuation is known and independent, the value of the good in a CVA is identical for all participants but uncertain prior to the sale. Bidders only receive private, imperfect signals about this true value. The core pedagogical hurdle in teaching CVAs is the "Winner's Curse": the realization that winning an auction implies one's private signal was the most optimistic in the room. Consequently, naive bidding leads to systematic overpayment.

Helping students transition from a superficial understanding of the Winner's Curse to modeling it mathematically is difficult. Standard CVA models with affiliated signals quickly become mathematically intractable, requiring students to navigate complex joint probability distributions and conditional expectations. Traditional lectures often result in students memorizing Nash equilibrium formulas without developing an intuitive grasp of why bid shading and signal conditioning are economically rational.

To overcome this, economics educators have increasingly turned to active learning and classroom experiments. Holt (1999) and Becker (1997) established that interactive games significantly improve student retention of counter-intuitive microeconomic concepts. Specifically, regarding auctions, Kagel and Levin (1986) provided seminal experimental evidence that even experienced bidders fall prey to the Winner's Curse. To teach this, instructors often use the classic "jar of coins" classroom experiment (Delemeester and Brauer, 2000). While these physical experiments successfully generate the Winner's Curse in real-time, they suffer from a critical limitation: it is exceedingly difficult to map the chaotic, small-sample outcomes of a physical classroom game to the rigorous, continuous-signal mathematical derivations required in advanced undergraduate or graduate coursework.

Simultaneously, a robust strand of literature has demonstrated the efficacy of computer simulations—particularly Monte Carlo methods—in economics education. Initially popularized in the teaching of econometrics, Monte Carlo simulations are highly effective at making abstract statistical theorems visible. Briand and Hill (2013) argue that Monte Carlo studies allow students to "see" the sampling distribution, transforming the abstract Law of Large Numbers and Central Limit Theorem into observable phenomena. Barreto and Howland (2006) further demonstrate that when students build or manipulate simulations themselves, their conceptual understanding of expected values and variance dramatically increases.

More recently, educators have extended computational simulations beyond econometrics into microeconomics and game theory. Simulations allow students to observe the long-run expected payoffs of different strategic choices without being bogged down by analytical integration. As Gremmen and Potters (1997) note, simulations serve as a bridge between simplified theoretical models and complex empirical realities. For game theory in particular, simulating millions of interactions helps students overcome behavioral biases—such as the failure to apply Bayes' rule or properly condition probabilities (Kahneman and Tversky, 1974)—by presenting them with undeniable empirical proof of suboptimal strategies. Highly related to this article, Runco (2025) shows how Monte Carlo simulations have been used to introduce Private Value Auctions to undergraduate students and provides evidence of its effectiveness in terms of student outcomes.

This article contributes to this pedagogical literature by combining the analytical tractability of a simplified CVA with the empirical power of Monte Carlo simulations. We propose a teaching methodology centered on the "Wallet Game," introduced by Klemperer (1998). The Wallet Game avoids the mathematical friction of affiliated signals by utilizing independent, uniformly distributed signals that linearly sum to the item's true value.

By utilizing the Wallet Game, instructors derive symmetric Nash equilibrium bidding functions on the blackboard for both Second-Price and First-Price auctions. We then provide a simple, robust Monte Carlo simulation script compatible with MATLAB and GNU Octave. This dual approach allows educators to bridge the gap identified in the literature: students can mathematically derive the optimal bid, and then use Monte Carlo simulations to empirically verify the theory. By examining small-sample simulated tables and large-sample convergence graphs, students can observe the losses caused by the Winner's Curse, solidifying their understanding of information aggregation in markets.

The Wallet Game Setup

Imagine a professor asks N students to participate in an auction for a prize. The prize's value is defined as the sum of the cash currently residing in all N students' wallets. Therefore, the true value is:

$$V = \sum_{j=1}^{N} X_j = X_i + \sum_{j \neq i}^{N} X_j$$

where X_i is the exact amount of money in student i's wallet (their private signal). We assume all signals X_i are drawn independent and identically distributed (i.i.d.) from a Uniform distribution on [0,1]. Let Y_i denote the highest signal among bidder i's N-1 opponents. The cumulative distribution function (CDF) of Y_1 is $G(y) = y^{N-1}$, with probability density function (PDF) g(y) = $(N-1)y^{N-2}$.

If we know that the maximum of the N-1 other signals is $Y_1 = y$, the remaining N-2 signals are uniformly distributed on [0, y]. The expected value of each remaining signal is y/2. Therefore, the expected value of the item conditional on a bidder's signal and the maximum opposing signal is:

$$E[V \mid X_i = x, Y_1 = y] = x + y + \frac{(N-2)y}{2} = x + \frac{N}{2}y$$

The Wallet Game Setup

3.1 Derivation via Pivotal Conditioning

In a sealed-bid SPA, a bidder should bid their expected value conditional on tying for the win. Because bidding functions are strictly increasing in a symmetric equilibrium, tying implies $X_i = Y_1 = x$. Substituting y = x into Equation 2 yields the equilibrium bid directly:

$$b^{SPA}(x) = E[V \mid X_i = x, Y_1 = x] = x + \frac{N}{2}x = x\frac{N+2}{2}$$

3.2 Derivation via Expected Payoff Maximization

We can confirm this result by maximizing the expected payoff. Suppose all N-1 opponents use a strictly increasing, differentiable symmetric strategy β(x). Bidder i with signal x places a bid b. They win if $b > \beta(Y_1)$, or $Y_1 < \beta^{-1}(b)$. Let $z = \beta^{-1}(b)$ be the “target signal” bidder i mimics. In an SPA, the winner pays the second-highest bid, which is $\beta(Y_1)$. The expected payoff is:

$$\Pi(z) = \int_0^z (E[V \mid X_i = x, Y_1 = y] - \beta(y))g(y)dy$$

Substituting Equation 2, we get:

$$\Pi(z) = \int_0^z \left(x + \frac{N}{2}y - \beta(y)\right)(N-1)y^{N-2}\,dy$$

Taking the derivative with respect to z (using Leibniz's rule) and setting the first-order condition to zero yields:

$$\frac{\partial \Pi}{\partial z} = \left(x + \frac{N}{2}z - \beta(z)\right)(N-1)z^{N-2} = 0$$

In a symmetric Nash equilibrium, the optimal target signal is the bidder's true signal, so z = x. This requires:

$$x + \frac{N}{2}x - \beta(x) = 0 \text{ then } \beta^{SPA}(x) = x\frac{N+2}{2}$$

This perfectly mirrors the pivotal conditioning derivation.

Imagine a professor asks N students to participate in an auction for a prize. The prize's value is defined as the sum of the cash currently residing in all N students' wallets. Therefore, the true value is:

Analytical Results: First-Price Auction (FPA)

4.1 Derivation via Expected Payoff Maximization

In a First-Price Auction, the winner pays their own bid b. Using the same target signal setup z = β^{-1}(b), the expected payoff is:

$$\Pi(z) = \int_0^z E[V \mid X_i = x, Y_1 = y] g(y) dy - \beta(z)\, G(z)$$

Substituting Equation 2 and rewriting:

$$\Pi(z) = \int_0^z \left(x + \frac{N}{2} y \right) g(y)\, dy - \beta(z)\, G(z)$$

Differentiating with respect to z yields the first-order condition:

$$\partial \Pi / \partial z = \left(x + \frac{N}{2} z \right) g(z) - \beta'(z) G(z) - \beta(z) g(z) = 0$$

Imposing the symmetric equilibrium condition z = x and rearranging:

$$\left(x + \frac{N}{2} x \right) g(x) = \beta'(x) G(x) + \beta(x) g(x)$$

Notice that the right side is exactly the derivative of the product β(x)G(x). Integrating both sides from 0 to x:

$$\beta(x) G(x) = \int_0^x s\, \frac{N+2}{2}\, g(s)\, ds$$

$$\beta(x) x^{N-1} = \frac{(N+2)(N-1)}{2} \int_0^x s^{N-1}\, ds$$

$$\beta(x) x^{N-1} = \frac{(N+2)(N-1)}{2} \left(\frac{x^N}{N} \right)$$

$$\beta^{FPA}(x) = x \frac{(N+2)(N-1)}{2N}$$

4.2 Derivation via Revenue Equivalence

This result can be rapidly confirmed using the Revenue Equivalence Theorem (RET). For the RET to hold across different auction formats, four primary conditions must be met: bidders must be risk-neutral, their private signals must be drawn independently from a common distribution, the equilibrium must assign the item to the bidder with the highest signal, and a bidder with the lowest possible signal must expect a payoff of exactly zero.

In our specification of the Wallet Game, these conditions are satisfied. The signals are i.i.d. Uniform, the symmetric and strictly increasing bidding strategies ensure the bidder with the highest signal always wins, and a bidder with an empty wallet (x=0) bids zero, guaranteeing zero expected profit. Therefore, the expected payment for a bidder with signal x must be identical across both the FPA and SPA formats.

The expected payment in the FPA is the probability of winning multiplied by the bid: $\beta^{FPA}(x)G(x)$. The expected value in the SPA is the expected value of the second-highest bid conditional on winning: $\int_0^x \beta^{SPA}(s)\, g(s)\, ds$. Equating the two:

$$\beta^{FPA}(x)\, G(x) = \int_0^x \beta^{SPA}(s)\, g(s)\, ds$$

$$\beta^{FPA}(x)x^{N-1} = \int_0^x s\,\frac{(N+2)(N-1)}{2}\, s^{N-2}\, ds$$

$$\beta^{FPA}(x)x^{N-1} = \frac{(N+2)(N-1)}{2}\int_0^x s^{N-1}\, ds$$

$$\beta^{FPA}(x)x^{N-1} = \frac{(N+2)(N-1)}{2N}\, x^N$$

$$\beta^{FPA}(x) = x\,\frac{(N+2)(N-1)}{2N}$$

This alternative derivation provides an excellent opportunity to teach students how standard auction theorems drastically simplify mathematical problem-solving, even in Common Value settings.

The Danger of Naive Bidding

A common misconception among students is that one should bid their unconditional expected value. In the Wallet Game, a “Naive” bidder assumes the N-1 other wallets hold the average amount (0.5). Their naive valuation is $V_{naive} = x + \frac{N-1}{2}$. Bidding this amount leads to systematically lower, and usually negative, profits in both formats due to the Winner's Curse.

In the SPA: The price paid is determined by the second-highest bid. If a naive bidder wins, it means they held the highest signal X_1. Consequently, the true value of the other N-1 wallets is likely much lower than the unconditional average of 0.5 because those signals are constrained to be less than X_1. The naive bidder pays a price based on the second highest signal Y_1, but since they failed to condition their valuation on the fact that $Y_1 \leq X_1$, the price paid frequently exceeds the true sum of the wallets.

In the FPA: Naive bidding is harmful for two compounding reasons. First, as in the SPA, the bidder falls victim to the Winner's Curse by overestimating the true value conditional on winning. Second, they completely fail to shade their bid. In an FPA, even if one's valuation is perfectly accurate, bidding one's exact valuation guarantees exactly zero profit. By combining an unshaded bid with an inflated valuation, the naive bidder guarantees themselves mathematically strictly negative expected profits.

Monte Carlo Simulations in MATLAB/Octave

To make the theory more concrete, we provide a robust, vectorized MATLAB/Octave script that simulates M auctions. It calculates the expected profits for the Nash equilibrium strategies derived above and compares them to the profits of naive bidders.

Crucially, to help students understand how expected payoffs are calculated empirically, the script isolates the first 10 auction realizations. We set the default number of bidders to N=2 so students can easily read the output and directly verify the analytical derivations from Sections 3.1 and 4.1 (i.e., observing that the equilibrium SPA bid is exactly $\boldsymbol{2x_i}$, and the FPA bid is exactly $\boldsymbol{x_i}$).

For readability, the script prints two separate, detailed tables (one for the SPA and one for the FPA) showing the randomly drawn signals, the equilibrium bids for both players, the true value of the wallet, who won, and the resulting payoff to three decimal places. It then calculates the sample average payoff for those 10 specific auctions, demonstrating the mechanics of expected values before outputting the aggregate results for the full 100,000 simulated auctions.

Listing 1: MATLAB/Octave Script for Wallet Game Simulations

```
% Wallet Game Monte Carlo Simulation
% Compatible with MATLAB and GNU Octave
clear; clc;

% Parameters
M = 100000; % Number of simulated auctions
N = 2;      % Number of bidders (Set to 2 to clearly see bids for both players)

% 1. Draw Signals and Calculate True Value
% Signals X are drawn from Uniform[0,1]
X = rand(M, N);
V = sum(X, 2); % True value of the wallet for each auction

% 2. Calculate Bids
% Equilibrium Bids (derived analytically)
B_SPA_Nash = X .* ((N + 2) / 2);
B_FPA_Nash = X .* (((N + 2) * (N - 1)) / (2 * N));

% Naive Bids: Unconditional expected value: x_i + E[sum(x_{-i})]
B_Naive = X + (N - 1) * 0.5;

% 3. Determine Winners and Prices
% SPA Price is the 2nd highest bid
[sorted_SPA_Nash, ~] = sort(B_SPA_Nash, 2, 'descend');
[sorted_Naive, ~]    = sort(B_Naive, 2, 'descend');
Price_SPA_Nash = sorted_SPA_Nash(:, 2);
Price_SPA_Naive = sorted_Naive(:, 2);

% FPA Price is the highest bid
[Price_FPA_Nash, ~]  = max(B_FPA_Nash, [], 2);
[Price_FPA_Naive, ~] = max(B_Naive, [], 2);

% 4. Calculate Profits for Winners
% Due to symmetric monotonic bidding, the winner has the highest signal
Profit_SPA_Nash  = V - Price_SPA_Nash;
Profit_FPA_Nash  = V - Price_FPA_Nash;
Profit_SPA_Naive = V - Price_SPA_Naive;
Profit_FPA_Naive = V - Price_FPA_Naive;

% 5. Detailed Look at the First 10 Realizations
[~, winner_id] = max(X(1:10, :), [], 2);
line_length = 31 + N*18; % Dynamic formatting length for 3 decimal places

% --- TABLE 1: Second-Price Auction (SPA) ---
fprintf('\n--- Table 1: First 10 Auctions (Second-Price Auction) ---\n');
fprintf('Auct | ');
for j = 1:N, fprintf(' Sig %d | ', j); end
for j = 1:N, fprintf(' Bid %d | ', j); end
fprintf(' Value | Win |  Payoff\n');
fprintf('%s\n', repmat('-', 1, line_length));

for i = 1:10
```

```
    fprintf('%4d | ', i);
    for j = 1:N, fprintf('%6.3f | ', X(i,j)); end
    for j = 1:N, fprintf('%6.3f | ', B_SPA_Nash(i,j)); end
    fprintf('%6.3f | %3d | %7.3f\n', V(i), winner_id(i), Profit_SPA_Nash(i));
end
fprintf('%s\n', repmat('-', 1, line_length));
fprintf('Average SPA Payoff (First 10 samples): %7.3f\n',
mean(Profit_SPA_Nash(1:10)));

% --- TABLE 2: First-Price Auction (FPA) ---
fprintf('\n--- Table 2: First 10 Auctions (First-Price Auction) ---\n');
fprintf('Auct | ');
for j = 1:N, fprintf(' Sig %d | ', j); end
for j = 1:N, fprintf(' Bid %d | ', j); end
fprintf(' Value | Win |  Payoff\n');
fprintf('%s\n', repmat('-', 1, line_length));

for i = 1:10
    fprintf('%4d | ', i);
    for j = 1:N, fprintf('%6.3f | ', X(i,j)); end
    for j = 1:N, fprintf('%6.3f | ', B_FPA_Nash(i,j)); end
    fprintf('%6.3f | %3d | %7.3f\n', V(i), winner_id(i), Profit_FPA_Nash(i));
end
fprintf('%s\n', repmat('-', 1, line_length));
fprintf('Average FPA Payoff (First 10 samples): %7.3f\n',
mean(Profit_FPA_Nash(1:10)));

disp(' ');
disp('This shows how the sample average expected payoff is built row by row.');

% 6. Display Large Sample Results
fprintf('\n--- Full Monte Carlo Results (M = %d, N = %d) ---\n', M, N);
fprintf('Average Winner Profit (Nash SPA): %f\n', mean(Profit_SPA_Nash));
fprintf('Average Winner Profit (Nash FPA): %f\n', mean(Profit_FPA_Nash));
fprintf('Average Winner Profit (Naive SPA): %f\n', mean(Profit_SPA_Naive));
fprintf('Average Winner Profit (Naive FPA): %f\n', mean(Profit_FPA_Naive));
disp('Notice how Naive strategies result in the Winners Curse (<0 profit).');
```

When instructors run this script live, students can track individual auctions row-by-row in the two tables. They can easily verify that the equilibrium bidding algorithms match the theory, see exactly how private signals aggregate into the true value, and observe the resulting payoff for the winner. Subsequently, observing the law of large numbers apply over 100,000 iterations reinforces the validity of the theoretical expected payoffs. Furthermore, students will clearly observe that Nash strategies yield positive expected profits, while naive strategies generate poor results—especially in the FPA, vividly confirming the danger of failing to condition bids.

Monte Carlo Simulations and Empirical Results

To bridge the gap between theory and observation, we implement a vectorized simulation in MATLAB/Octave. We first examine a small sample of 10 auctions with N=2 bidders to allow students to trace the mechanics of bids and payoffs row-by-row. Table 1 and Table 2 present these realizations using the equilibrium strategies derived in the previous sections.

Table 1: First 10 Auction Realizations: Second-Price Auction (SPA)

Auct.	Sig 1	Sig 2	Bid 1 ($2x_1$)	Bid 2 ($2x_2$)	Value	Win	Payoff
1	0.742	0.588	1.484	1.177	1.330	1	0.154
2	0.240	0.604	0.480	1.207	0.844	2	0.364
3	0.285	0.147	0.571	0.294	0.433	1	0.138
4	0.382	0.902	0.765	1.804	1.284	2	0.520
5	0.429	0.551	0.858	1.101	0.979	2	0.122
6	0.096	0.812	0.192	1.623	0.908	2	0.716
7	0.341	0.722	0.682	1.444	1.063	2	0.381
8	0.309	0.974	0.617	1.947	1.282	2	0.665
9	0.754	0.820	1.508	1.640	1.574	2	0.066
10	0.568	0.451	1.136	0.901	1.019	1	0.117
Average SPA Payoff (First 10 samples):							0.324

Table 2: First 10 Auction Realizations: First-Price Auction (FPA)

Auct.	Sig 1	Sig 2	Bid 1 (x_1)	Bid 2 (x_2)	Value	Win	Payoff
1	0.742	0.588	0.742	0.588	1.330	1	0.588
2	0.240	0.604	0.240	0.604	0.844	2	0.240
3	0.285	0.147	0.285	0.147	0.433	1	0.147
4	0.382	0.902	0.382	0.902	1.284	2	0.382
5	0.429	0.551	0.429	0.551	0.979	2	0.429
6	0.096	0.812	0.096	0.812	0.908	2	0.096
7	0.341	0.722	0.341	0.722	1.063	2	0.341
8	0.309	0.974	0.309	0.974	1.282	2	0.309
9	0.754	0.820	0.754	0.820	1.574	2	0.754
10	0.568	0.451	0.568	0.451	1.019	1	0.451
Average FPA Payoff (First 10 samples):							0.374

To underscore the danger of the Winner's Curse, we contrast the equilibrium results with a scenario where both bidders employ a “Naive” strategy. A naive bidder bids their unconditional expected value of the item, which is their own signal plus the average expected value of the opponent's signal ($\boldsymbol{x}_i + \mathbf{0.5}$).

Tables 3 and 4 present the outcomes for the exact same 10 signal realizations when bidders act naively.

Table 3: First 10 Auction Realizations: Naive SPA Strategy ($b_i = x_i + 0.5$)

Auct.	**Sig 1**	**Sig 2**	**Bid 1 (x_1+0.5)**	**Bid 2 (x_2+0.5)**	**Value**	**Win**	**Payoff**
1	**0.742**	**0.588**	**1.242**	**1.088**	**1.330**	**1**	**0.242**
2	**0.240**	**0.604**	**0.740**	**1.104**	**0.844**	**2**	**0.104**
3	**0.285**	**0.147**	**0.785**	**0.647**	**0.433**	**1**	**-0.214**
4	**0.382**	**0.902**	**0.882**	**1.402**	**1.284**	**2**	**0.402**
5	**0.429**	**0.551**	**0.929**	**1.051**	**0.979**	**2**	**0.050**
6	**0.096**	**0.812**	**0.596**	**1.312**	**0.908**	**2**	**0.312**
7	**0.341**	**0.722**	**0.841**	**1.222**	**1.063**	**2**	**0.222**
8	**0.309**	**0.974**	**0.809**	**1.474**	**1.282**	**2**	**0.473**
9	**0.754**	**0.820**	**1.254**	**1.320**	**1.574**	**2**	**0.320**
10	**0.568**	**0.451**	**1.068**	**0.951**	**1.019**	**1**	**0.068**
Average Naive SPA Payoff (First 10 samples):							**0.198**

Table 4: First 10 Auction Realizations: Naive FPA Strategy ($b_i = x_i + 0.5$)

Auct.	Sig 1	Sig 2	Bid 1 (x_1+0.5)	Bid 2 (x_2+0.5)	Value	Win	Payoff
1	0.742	0.588	1.242	1.088	1.330	1	0.088
2	0.240	0.604	0.740	1.104	0.844	2	-0.260
3	0.285	0.147	0.785	0.647	0.433	1	-0.352
4	0.382	0.902	0.882	1.402	1.284	2	-0.118
5	0.429	0.551	0.929	1.051	0.979	2	-0.072
6	0.096	0.812	0.596	1.312	0.908	2	-0.404
7	0.341	0.722	0.841	1.222	1.063	2	-0.159
8	0.309	0.974	0.809	1.474	1.282	2	-0.192
9	0.754	0.820	1.254	1.320	1.574	2	0.254
10	0.568	0.451	1.068	0.951	1.019	1	-0.049
Average Naive FPA Payoff (First 10 samples):							-0.126

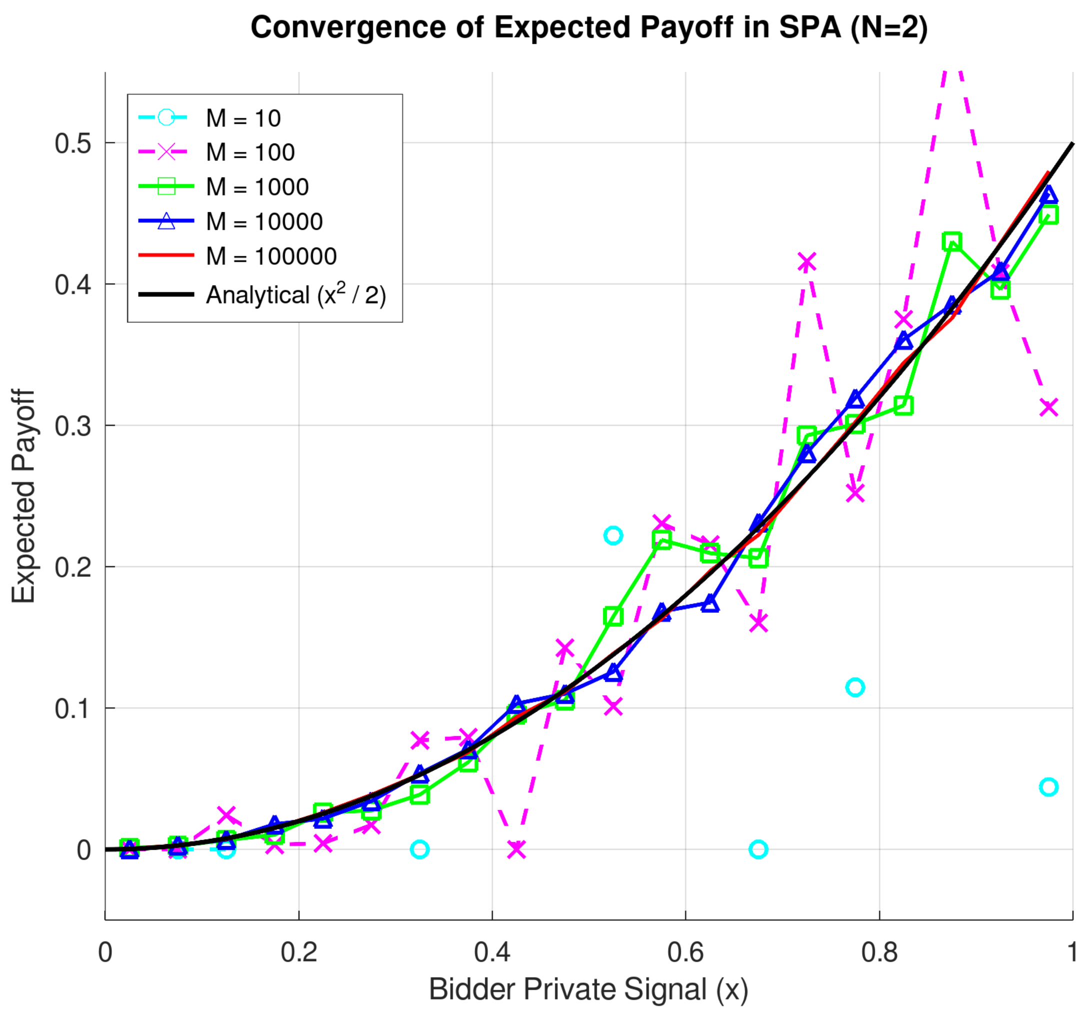
By juxtaposing the rational and naive tables, students can empirically observe the mechanics of the Winner's Curse. In the Naive SPA (Table 3), Bidder 1 wins Auction 3 but suffers a negative payoff. This occurs because Bidder 1 assumed Bidder 2 held an average wallet ($0.50), when in reality Bidder 2 held a mere $0.147.

The consequences are even more severe in the Naive FPA (Table 4). Because bidders pay their unshaded bids, overestimating the opposing signal guarantees financial losses. In 8 out of the 10 realizations, the winner of the naive FPA loses money, demonstrating why conditional expected valuation and bid shading are critical for good results.

7.1 Convergence to Analytical Payoffs

While individual auction rows demonstrate the mechanics, the Law of Large Numbers is required to verify the equilibrium properties. Figure 1 illustrates the convergence of the empirical expected payoff to the analytical closed-form result. For N=2 and $x \in [0,1]$, the theoretical expected payoff for a bidder with signal x is $\Pi(x) = x^2/2$.

By increasing the number of simulated auctions from M=10 to M=100,000, students can observe how the small sample averages eventually smooth out to match the theoretical curve. This visualization is particularly useful for demonstrating that Nash equilibria are not just abstract formulas but predictors of long-run average outcomes in competitive environments.



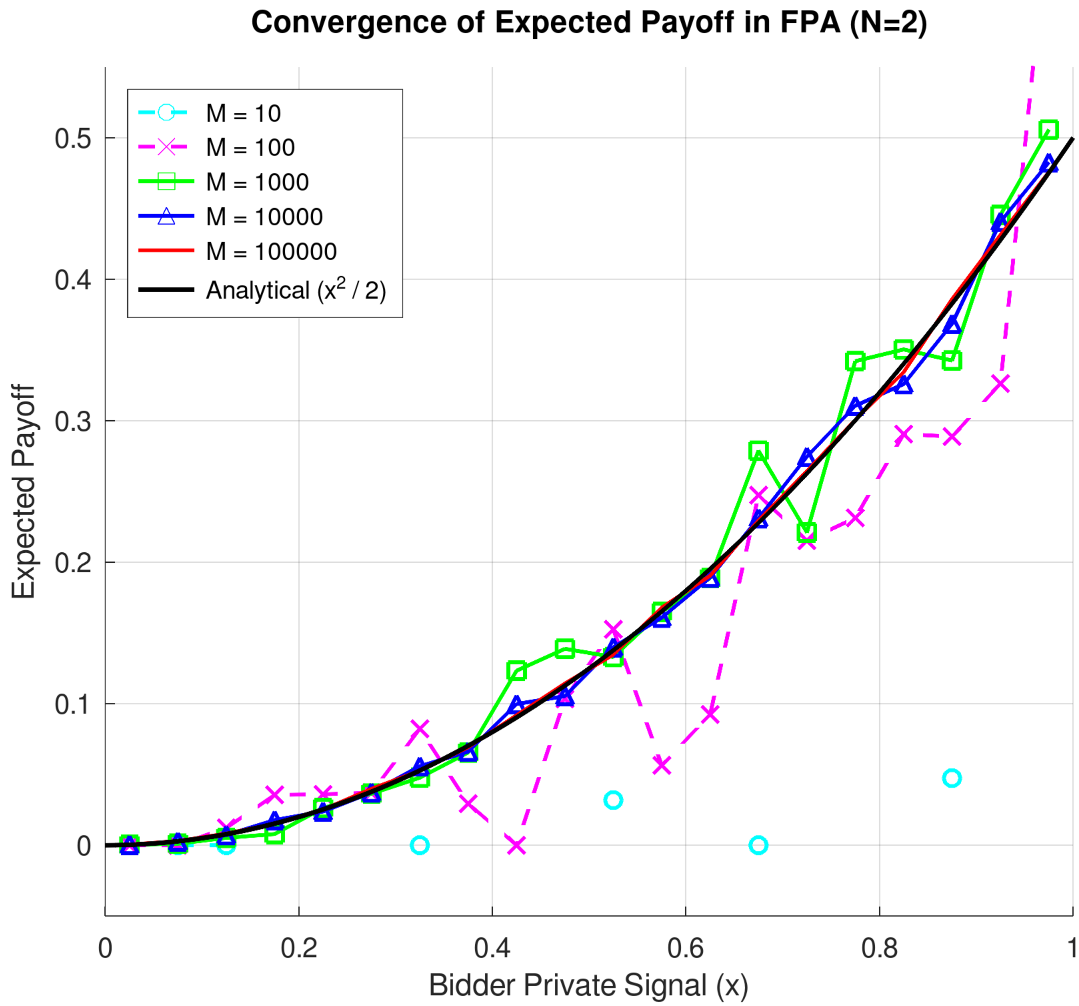


Figure 1: Empirical expected payoff convergence. The noisy lines represent low-sample simulations (M=10; 100; 1,000 and 10,000), while the M=100,000 simulation aligns with the analytical solution (black line).

7.2 Large Sample Comparisons and the Winner's Curse

Using M=100,000 simulations, we compare the Nash Equilibrium strategies against a Naive strategy (bidding x + 0.5). The results for N=2 are summarized below:

- **Average Profit (Nash SPA):** 0.3337
- **Average Profit (Nash FPA):** 0.3332
- **Average Profit (Naive SPA):** 0.1670
- **Average Profit (Naive FPA):** -0.1667

The results highlight that while naive bidders might survive a Second-Price Auction due to the pricing rule, they face large losses in a First-Price Auction. In the FPA, the combination of an inflated valuation (Winner's Curse) and a failure to shade the bid leads to a strictly negative average profit.

Conclusion

Teaching Common Value Auctions requires balancing rigorous game-theoretic concepts with intuitive economic mechanisms. The Wallet Game serves as an exceptional pedagogical vehicle for this task. As demonstrated, the assumption of uniformly distributed signals allows instructors to derive relatively simple, linear bidding functions for both First- and Second-Price auctions using both pivotal reasoning and direct payoff maximization.

Furthermore, supplementing the blackboard mathematics with the provided MATLAB/Octave simulation code empowers students to empirically verify the theory. Seeing the “Naive” bidding strategy systematically yield negative returns clarifies their understanding of the mechanics of the Winner's Curse. This combined analytical and computational approach effectively demystifies Common Value Auctions, providing a robust template for undergraduate and introductory graduate economics curricula.

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Valuing College Athletes in the N.I.L. Era

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Introduction

The modem landscape of college athletics has drastically changed. Gone are the days where student-athletes were explicitly student-athletes. Student athletes are now able to profit off of their Name, Image, and Likeness (NIL) following the decision in *NCAA v. Alston* (Harvard Law Review, 2021). College sports has evolved into a billion dollar industry, with a rapid jump in revenues from 2023 to 2024 and even more revenues expected in 2025 (Berkowitz, 2025).

Despite the exuberant revenues, universities are still unable to pay their student athletes directly under the current NCAA rules. However, significant traction has been gained for a revenue-sharing in which universities will soon be able to pay student-athletes. As part of a proposed settlement in the *House v. NCAA* lawsuit, universities will soon be able to pay athletes directly (Knight Commission on Intercollegiate Athletics, 2025).

The move from no compensation for student-athletes to full-on pay-for-play has happened rapidly in college athletics. The rapid changes have left the NCAA and universities scrambling to come up with solutions. Admist the chaos surrounding college athletics, accountants have a significant opportunity to expand their services into the NIL and revenue-sharing space.

This research paper will seek to point out the ways in which accountants can provide to universities and student-athletes. By focusing on consulting and business valuation services, this paper will identify key issues in the current state of college athletics that these services will be of the most value. Through consulting services, accountants can help universities with the interpretation and application of the new revenue-sharing model proposed in *House v. NCAA.* Business valuation methodology can help the universities determine the fair-market value of athletes and each different sport overall. The combination of consulting and business valuation services will allow accountants to create a sustainable model of navigating this new era of college athletics.

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Consulting Services for Application of Proposed Revenue-Sharing Model

As part of the settlement in the *House v. NCAA* lawsuit, both sides have reportedly agreed to a revenue-sharing model that will soon be adopted by universities (Knight Commission on Intercollegiate Athletics, 2025). Athletic departments will essentially be operating with a limited cap space to allocate to their different sports. They will be operating in a similar manner to professional sports organizations, albeit with much less experience. The limited amount of money that athletic departments will have available to allocate will need to be done so in a smart, and efficient manner.

In a recent statement released by the NCAA, further details were provided about the proposed revenue-sharing model. The settlement is still pending final approval, however, significant progress has been made with regards to more rules and more structure surrounding NIL and revenue-sharing in college sports. The statement from the NCAA reads:

"The proposed settlement would facilitate meaningful opportunities for student-athletes to further benefit from their participation in intercollegiate athletics, while establishing a robust system of oversight and controls to ensure fair competition and protect the integrity of collegiate athletics and the best interests of student athletes, participating institutions and fans" (NCAA Media Center, 2025, para. 2).

Increased oversight and structure were two of the biggest areas of concern surrounding college athletics and now the NCAA seemingly has a plan to address it.While the settlement is still pending, now is the time for athletic departments and universities to seek out consulting services from accounting firms. Accounting consulting engagements can help the universities to take the revenue-sharing model proposed and apply it to its athletic department. By engaging the accounting firms at the onset of the application, the process will be much smoother as opposed to engaging the accounting firm after months of failed application.

Business Valuations and Allocating Resources

Now that universities and athletic departments know they are facing a salary cap situation, they must determine how to allocate the revenues. One major question facing universities and athletic departments is how to properly allocate the revenues between the different sports and athletes. To properly allocate revenues between different athletes and sports, universities must know the fair value of each. Universities must balance equitable allocation of revenues with the fact that not every sport at the university has the same value. The value of the football team at a university will be different than the baseball team (Zimbalist, 2023).

Much like how business valuations are used to determine how much a business is worth before it is sold, business valuations can be used to determine how much each sport is worth at a university. Accountants can use economic analysis in their valuation of how much each sport is worth. This economic analysis can be achieved using revenues from TV deals, ticket sales, merchandise sales, and social media presence (Zimbalist, 2023). Further analysis can be done to compare the different sports teams with those in their respective athletic conferences. Big Ten schools can be compared to other Big Ten schools and SEC schools can be compared to other SEC schools.

Universities and athletic departments also have certain policies, like Title IX, to consider when allocating revenues between different sports. NIL opportunities from university collectives and donors overwhelmingly favor men's sports, and the majority of NIL opportunities for female athletes come from brands themselves (Opendorse, 2023, pg. 3). Unlike the practices conducted by donors and collectives, revenue-sharing will need to be mindful of Title IX and other equity rules since the revenues are distributed directly by the universities. The same revenue sharing opportunities afforded to men's sports must be given to women's sports (Lovell, 2025). Business valuation methodology will help universities navigate Title IX and equity compliance to ensure that revenues are distributed equitably between men's and women's sports.

Problems with the Current NIL Structure

Each position of each sport is going to have a different value. Under the current NIL model, incoming college freshmen, like AJ Dybantsa at BYU, are getting deals reportedly worth millions of dollars (Norlander, 2024). Furthermore, the 2025 national champions Ohio State football team spent around Twenty million dollars on their collective roster (Salemo, 2024).

How did BYU determine an incoming freshman was worth millions? How did Ohio State Football determine how to allocate the twenty-million between the different players in its roster? Without true market values for each sport and each position, universities and athletic departments are left to determine an athlete's worth without full market research.

Determining Student-Athlete Fair Market Value

Business valuations are centered around ultimately determining what something is worth, whether it be a business or some other asset that is up for sale. Given that the fair value of what each athlete is worth is not a readily available amount there needs to be some way to value the student-athletes.

Players and agents negotiate NIL deals and transfer agreements, but in no way does the process resemble the models present in professional sports. Many of the NIL deals received by student-athletes are predicated on their popularity or brand (Fortunato, 2025). The NFL, for example, has a players' union which in turn has a collective bargaining agreement with the NFL that helps to create a fair market for the athletes and the organizations (National Football League Players Association, 2020).

Players and universities alike would greatly benefit from a system like this in college athletics. Using the analysis and tactics found in business valuations, accountants can help athletes and universities to determine Fair Market Value.

Business Valuation tactics would also help universities come up with a specific value for each different position in each sport.

Business valuation tactics could look at each player by position and come up with a value associated with each position. Using a combination of different analyses and valuation calculations, accountants would be able to determine fair market value for each athlete. Financial analysis, economic analysis, industry analysis, and valuation research are all different methods that accountants can use when conducting the business valuation for the athletic departments (Sanli, 2024). These valuation methods would provide Athletic departments with tangible evidence and analysis as to how much they need to allocate for each position and sport.

Conclusion

In conclusion, the rapid evolution of college sports presents many opportunities for accountants. Accountants can offer universities a wide-range of services that will help with the transition to a new model of college-athletics. Helping universities apply the new revenue-sharing model as a consulting engagement is an area where accountants can offer their service. Valuation services in particular will be key in helping universities determine how to pay their student-athletes fairly and accurately. The tactics and methods of business valuations will allow universities to tangibly value their different sports and athletes. The new world of college sports offers uncertainty, but accountants are equipped with the necessary skills and services to help ease the uncertainty for athletes and universities.

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