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Consumer Sentiment and Spending in Extreme Events

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We examine tail dependence between consumer sentiment and spending during crises, focusing on COVID-19 and the Global Financial Crisis. Using copula models on U.S. monthly data from 2003–2024, we quantify extreme co-movements and find asymmetric tail dependence that intensifies during crises: upper-tail dependence rises to 0.35 post-pandemic, 3.5 times its pre-pandemic level, while the financial crisis shows stronger lower-tail dependence. A Bayesian VAR framework highlights the role of macroeconomic factors. The economic significance is noteworthy: extreme optimism corresponds to a 2.8 percentage-point increase in spending growth, and fiscal multipliers are amplified by 40–60% during sentiment rebounds. These results underscore the value of tail dependence analysis for stabilization policy and crisis-specific risk management.

Keywords: Sentiment, copula modeling, dependence, extreme events, uncertainty

JEL Classifications: C51, E21, G01

1 Introduction

The relationship between consumer sentiment and economic activity is central to interdisciplinary research. The notion of "animal spirits" introduced by Keynes (1936) highlights how spontaneous optimism and emotional drivers influence economic decision-making. Contemporary research extends these insights, exploring cognitive biases and emotional factors in market behavior (Akerlof and Shiller, 2009; Farmer, 2012; Middleton, 1996; Nguyen and Claus, 2013).

While the link between consumer confidence and spending is well-established (Bram and Ludvigson, 1998; Kwan and Cotsomitis, 2006; Eppright et al., 1998), prior work has mainly focused on average relationships or specific nonlinearities. A gap remains in understanding the distributional aspect, especially how sentiment and spending co-move during extreme events.

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Extreme events, defined as periods when sentiment or spending growth falls in the top or bottom 10% of their historical distributions, such as the Global Financial Crisis (GFC) and COVID-19 pandemic, often lead to behavioral shifts (Mian et al., 2017; Knotek et al., 2020). The present study addresses this gap by using copulas to quantify tail dependence between sentiment and spending, or the probability of extreme co-movements during crises.

We use a two-step procedure. First, we model the individual dynamics of sentiment (University of Michigan Consumer Sentiment Index) and spending (real Personal Consumption Expenditures) with autoregressive integrated moving average models. Second, we use copulas to connect these univariate distributions into a joint framework that captures dependence structures. Copulas are effective for examining dependency patterns, especially tail dependencies that become pronounced during extreme events. We also use a Bayesian vector autoregressive (BVAR) model to examine how macroeconomic factors such as unemployment, income, inflation expectations, yield spread, and uncertainty shape sentiment and spending patterns.

Our empirical analysis uses monthly data from January 2003 to January 2024, split into pre- and post-pandemic periods to examine COVID-19's impact. We find a significant shift in the dependence structure post-pandemic, with pronounced asymmetry in tail dependence. Upper-tail dependence increases to 0.35 post-pandemic, a 3.5-fold rise from the pre-pandemic period, indicating a high probability of extreme spending co-occurring with extreme optimism during crises. In contrast, lower-tail dependence remains modest at 0.10. The BVAR analysis shows that economic shocks cause sharp declines in sentiment followed by gradual recoveries. We also translate these findings into economic significance. Extreme optimism corresponds to a 2.8 percentage-point increase in annual spending growth, or $460 billion, and fiscal policy multipliers are amplified by 40–60% during sentiment rebounds.

This study makes several contributions. We introduce copula-based extreme value analysis to quantify tail dependence between sentiment and spending during crises, capturing extreme co-movements. We provide the first comparative analysis of dependence structures across two fundamentally different crises, the GFC and COVID-19, revealing crisis-specific tail dependence patterns. We also translate statistical dependence into economic measures, showing how much stronger the relationship becomes in crisis tails and quantifying implications for policy effectiveness. These results connect consumer behavior research with recent contributions in extreme value theory and information-theoretic dependence measures (Genest and Rémillard, 2004; Durante et al., 2022), using the transformed-linear local likelihood copula to capture asymmetric tail dependence without parametric assumptions. These contributions offer guidance for stabilization policy and business strategy during crises.

The paper is organized as follows. Section 2 reviews recent literature on consumer sentiment. Section 3 details the copula framework for analyzing extremal dependence. Section 4 presents findings for COVID-19, and Section 5 compares these with the GFC. Section 6 studies resilience using a BVAR model. Section 7 discusses implications, and Section 8 concludes.

2 Background

Research on consumer sentiment and spending dates to Keynes' (1936) "animal spirits" concept, highlighting how psychological factors influence economic decisions (Akerlof and Shiller, 2009; Farmer, 2012; Keynes, 1936). Sentiment indices predict economic activities (Abeele, 1983; Barsky and Sims, 2012; Ludvigson, 2004) and future expenditures (Bram and Ludvigson, 1998; Eppright et al., 1998; Kwan and Cotsomitis, 2006), with the impact varying across economic regimes (Ahmed and Cassou, 2016). Recent work distinguishes rational from irrational sentiment (Gric et al., 2022) and examines sentiment's dynamic responses to shocks (Elmassah and Hassanein, 2020).

During the COVID-19 pandemic, studies highlight rapid sentiment shifts (Buckman et al., 2020) and region-specific responses (Teresiene et al., 2021). Behavioral research shows how social networks influence spending (Kuchler and Stroebel, 2021) and how sentiment immediately impacts discretionary spending (Bianchi et al., 2022), with rapid preference changes linked to confidence fluctuations (Goolsbee and Syverson, 2021). Alternative data sources like news sentiment forecast inflation (Eugster and Uhl, 2024) and consumer confidence (Qiu, 2020). Determinants of sentiment include financial and non-financial variables (Alaoui et al., 2020), while incorporating real income improves spending forecasts (Gutjahr, 2024). Information about government responses alters consumer expectations during crises (Bui et al., 2023). Studies document asymmetries in the sentiment-consumption relationship, with different responses pre- and during-COVID-19 (Abosedra et al., 2021) and strategic implications for businesses (Liu, 2023). Systemic risk affects GDP growth through sentiment channels (Kanas and Zervopoulos, 2021), suggesting policies targeting sentiment can mitigate adverse economic effects.

While this literature establishes nonlinearities and asymmetries in the sentiment-spending relationship, it does not quantify tail dependence. Tail dependence refers to the probability of extreme co-movements during crises. Copula methods are widely used in finance and risk management (Genest and Rémillard, 2004; Joe, 2014) and can offer this capability. However, these methods have not been applied to sentiment-spending dynamics. Recent advances in extreme value theory and information-theoretic dependence measures (Durante et al., 2022; Oh and Patton, 2023) provide tools for capturing crisis-specific patterns. Our study bridges this gap by applying copula models to measure tail dependence between sentiment and spending during the Global Financial Crisis and COVID-19.

3 Extremal dependence

Copula-based approaches are chosen for their flexibility and robustness in modeling nonlinear and extremal dependencies. We define extreme events as periods where the standardized sentiment or spending growth falls in the top or bottom 10% of its historical distribution, following the quantile-based approach of extreme value theory (Joe, 2014). Crises are extreme events that coincide with major economic shocks: the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020–2021), identified via structural break tests and economic narrative. Uncertainty is measured by the economic policy uncertainty index of Baker et al. (2016), which combines news coverage, tax code expirations, and forecaster disagreement.

The dependence between consumer sentiment and spending is captured via copulas, which separate marginal distributions from the dependence structure. For random variables $x_1, \ldots, x_d$ with continuous marginal CDFs F_i and joint CDF F, Sklar's theorem (Sklar, 1959) states that a unique copula C exists such that

$$F(x_1, \ldots, x_d) = C(F_1(x_1), \ldots, F_d(x_d)). \tag{1}$$

The corresponding joint density is

$$f(x_1, \ldots, x_d) = c(F_1(x_1), \ldots, F_d(x_d)) \prod_{i=1}^{d} f_i(x_i), \tag{2}$$

where c is the copula density. This separation allows flexible modeling of dependence, including tail dependence, which is the probability of extreme co-movements:

$$\lambda_U = \lim_{u \to 1} \Pr[U > u \mid V > u], \qquad \lambda_L = \lim_{u \to 0} \Pr[U \leq u \mid V \leq u], \tag{3}$$

where $U = F_1(x_1)$ and $V = F_2(x_2)$ are uniform transforms.

We employ the transformed-linear local likelihood (TLL2nn) copula (Yan, 2007; Kojadinovic and Yan, 2010), a semiparametric copula that combines parametric and nonparametric elements to flexibly model asymmetric tail dependence without imposing restrictive functional forms. This copula is suitable for our context because: (1) it captures different dependence patterns in the upper and lower tails, which is essential for crisis periods where optimistic and pessimistic consumers may react differently; (2) it adapts to data patterns via local polynomial smoothing, making it robust to the unprecedented nature of COVID-19; and (3) it does not assume symmetry or elliptical shapes, allowing it to reveal crisis-specific dependence structures that standard parametric copulas (Gaussian, t, Clayton, Gumbel, etc.) might miss.

The copula is estimated by maximum likelihood. For observations $\{u_{i,1}, u_{i,2}\}_{i=1}^{N}$, the log-likelihood is

$$\mathcal{L}(\Theta) = \sum_{i=1}^{N} \log c(u_{i,1}, u_{i,2} \mid \Theta) + \sum_{i=1}^{N} \sum_{j=1}^{2} \log f_j(x_{i,j} \mid \Theta_j), \tag{4}$$

where Θ collects all parameters. Model selection among candidate copula families uses the Akaike and Bayesian information criteria (AIC, BIC), defined as

$$\text{AIC} = -2\mathcal{L}(\hat{\Theta}) + 2k, \qquad \text{BIC} = -2\mathcal{L}(\hat{\Theta}) + k \log N, \tag{5}$$

where k is the number of parameters.

The copula approach offers distinct advantages over methods used in prior sentiment–spending research. Unlike threshold or regime-switching models that conflate changes in marginals with changes in dependence, copulas separately model marginal dynamics and dependence structure. This is crucial during crisis periods, when both marginals and their interdependence shift dramatically. While existing studies note asymmetries, copulas provide explicit measures of upper- and lower-tail dependence coefficients (λ_U, λ_L), quantifying the probability that sentiment and spending experience extreme movements simultaneously. Recent studies in financial economics have successfully applied copula methods to study extreme dependence in asset returns (Oh and Patton, 2023) and systemic risk (Ardakani, 2023), but these methods have not been applied to the sentiment–spending relationship. Our study bridges this gap while providing insights into consumer behavior during crises.

We adopt a two-step estimation procedure. First, we model the marginal distributions of consumer sentiment and spending using autoregressive integrated moving average (ARIMA) models. The ARIMA(p, d, q) specification for a series r_t is

$$(1 - L^d)r_t = c + \phi(L)r_t + \theta(L)\varepsilon_t, \tag{6}$$

where L is the lag operator, $\phi(L)$ and $\theta(L)$ are polynomials of orders p and q, and ε_t is white noise. The orders (p, d, q) are selected via the Hyndman–Khandakar algorithm (Hyndman and Khandakar, 2008), which uses successive KPSS tests (Kwiatkowski et al., 1992) to determine d and minimizes AIC to choose p and q.

Second, we fit the copula to the probability integral transforms $U_t = F_1(r_{1,t} \mid \hat{\Theta}_1)$ and $V_t = F_2(r_{2,t} \mid \hat{\Theta}_2)$ from the estimated marginal models. This two-step approach helps validate the marginal models before estimating dependence, which supports reliable copula inference.

4 Impacts of the COVID-19 pandemic

4.1 Data

We use monthly data from January 2003 to January 2024. Sntiment is measured by the University of Michigan Consumer Sentiment Index (CSI), a widely recognized gauge of US consumer confidence (Curtin, 1982; Ludvigson, 2004). Spending is measured by real Personal Consumption Expenditures (PCE) from the US Bureau of Economic Analysis, expressed as year-over-year percent changes. To study the impact of COVID-19, we split the sample in March 2020, when the WHO declared a global health emergency. To achieve stationarity we use percent-change series. We verify stationarity and structural breaks with augmented Dickey–Fuller, Phillips–Perron, and Bai–Perron tests; results confirm a significant break in March 2020 for both series, justifying the sample split. Robustness checks using alternative marginal models and spending measures yield unchanged dependence estimates.

Table 1 presents summary measures for the CSI and PCE growth, illustrating the shifts in consumer confidence and spending following the onset of COVID-19. The CSI exhibits a pronounced downturn, with its average percent change declining from 1.22 in the pre-pandemic period to -7.56 post-pandemic. In contrast, PCE growth shows a robust increase, rising from an average of 4.04% to 7.00%. Standard deviations for both series increase substantially after March 2020, reflecting heightened volatility in consumer behavior during the pandemic. The distributional characteristics also change. CSI skewness shifts from -0.09 to 0.53, indicating a more asymmetric distribution with a longer left tail, while PCE maintains a rightward skew (1.04 for the entire sample) and exhibits heavy tails, as evidenced by a kurtosis of 15.16.

Table 1: Summary statistics for sentiment and spending growth

Statistics	Consumer Sentiment Index			Real Personal Expenditure		
	Entire	Pre	Post	Entire	Pre	Post
Mean	-0.37	1.22	-7.56	4.58	4.04	7.00
SD	14.11	12.45	18.48	3.68	2.00	7.09
Min	-41.52	-33.88	-41.52	-14.36	-3.36	-14.36
Median	0.47	1.71	-13.12	4.48	4.35	6.84
Max	38.80	35.86	38.80	29.65	7.49	29.65
Skewness	-0.12	-0.09	0.53	1.04	-1.71	0.01
Kurtosis	3.21	3.68	2.53	15.16	6.96	5.28

Monthly data from January 2003 to January 2024 (253 observations). Percent changes from a year ago are used. Pre and Post refer to pre- and post-pandemic samples (split at March 2020).

Figure 1 plots the time series of CSI and PCE growth, visually confirming the divergence in their post-pandemic trajectories. The CSI shows a sharp decline in mid-2020 followed by a volatile recovery, while PCE experiences a dramatic drop and subsequent surge. The increased dispersion in both series, particularly for PCE, is consistent with the elevated standard deviations reported in Table 1.

We evaluate the stationarity properties of both series using augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, with results reported in Table 2. For the post-pandemic CSI, the ADF and PP tests cannot reject the unit root null at the 5% significance level, while the KPSS test rejects the null of stationarity. This evidence supports modeling post-pandemic sentiment as an ARIMA(0,1,0) process, a random walk, which aligns with the notion that consumer expectations were subject to unpredictable shocks during the pandemic. In contrast, pre-pandemic sentiment appears trend-stationary. For PCE, both pre- and post-pandemic series reject the unit root null at conventional levels. We also test for structural breaks using the Bai-Perron and Chow tests, which identify a statistically

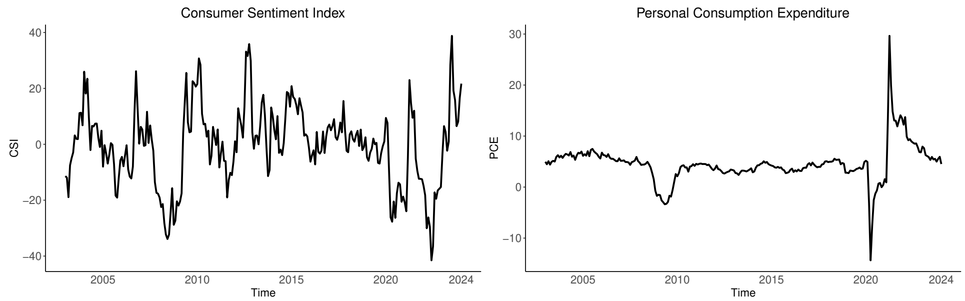

Figure 1: Time series of CSI and PCE growth

significant break in March 2020 for both series (Chow test F-stats of 28.7 for CSI and 19.4 for PCE, both with $p < 0.001$), validating our sample split.

Table 2: Unit root and stationarity tests

	Pre-pandemic (2003–2019)			Post-pandemic (2020–2024)		
Series	ADF	PP	KPSS	ADF	PP	KPSS
CSI (level)	-3.21*	-3.18*	0.12	-2.89	-2.87	0.45**
CSI (1st diff)	-6.45***	-6.48***	0.04	-5.67***	-5.71***	0.06
PCE (level)	-4.12***	-4.10***	0.08	-3.98**	-3.95**	0.11
PCE (1st diff)	-7.89***	-7.92***	0.03	-6.54***	-6.58***	0.05

***, **, * denote significance at 1%, 5%, and 10% levels. For ADF and PP tests, the null hypothesis is a unit root; for KPSS, the null is stationarity. Critical values from MacKinnon (2010).

4.2 Findings

We estimate ARIMA models for each series and subsample using the Hyndman-Khandakar algorithm, which selects the differencing order d via successive KPSS tests and chooses the autoregressive and moving average orders (p and q) by minimizing the AIC. The resulting specifications and estimates are presented in Table 3. For CSI, the pre-pandemic period is best modeled as ARIMA(1,0,0), indicating persistence in sentiment, while the post-pandemic period follows an ARIMA(0,1,0) (random walk). For PCE, the pre-pandemic specification is ARIMA(0,1,0), and the post-pandemic specification is ARIMA(1,0,1). The log-likelihood, AIC, BIC, and root mean squared error (RMSE) are reported for each model. The increase in RMSE for CSI post-pandemic (9.65 versus 7.06 pre-pandemic) reflects greater unpredictability during the crisis, while the RMSE for PCE also rises post-pandemic, albeit from a lower base.

Table 3: Maximum-likelihood estimates from ARIMA models

	Entire sample	Pre-pandemic	Post-pandemic
Consumer Sentiment Index			
Model type	ARIMA(1,0,1)	ARIMA(1,0,0)	ARIMA(0,1,0)
Selection criterion	AIC = 1745.99	AIC = 1401.62	AIC = 334.70
	BIC = 1761.44	BIC = 1411.05	BIC = 339.05
Unit root test (ADF)	-3.21*	-3.25*	-2.89
KPSS test	0.12	0.11	0.45**
Ljung–Box p-value	0.18	0.22	0.31
$\log \mathcal{L}$	-869.99	-698.81	-166.35
RMSE	7.52	7.06	9.65
Real Personal Consumption Expenditure			
Model type	ARIMA(1,0,3)	ARIMA(0,1,0)	ARIMA(1,0,1)
Selection criterion	AIC = 996.14	AIC = 476.52	AIC = 253.90
	BIC = 1021.17	BIC = 480.86	BIC = 263.32
Unit root test (ADF)	-4.12***	-4.08***	-3.98**
KPSS test	0.08	0.07	0.11
Ljung–Box p-value	0.24	0.35	0.28
$\log \mathcal{L}$	-492.07	-237.26	-123.95
RMSE	1.69	0.76	3.49

The log-likelihood is denoted by $\log \mathcal{L}$. AIC and BIC are information criteria. RMSE is the root mean squared error. For the ADF test, the null hypothesis is a unit root. For the KPSS test, the null hypothesis is stationarity. The Ljung-Box test evaluates residual autocorrelation with null of no autocorrelation. ***, **, and * are the 1%, 5%, and 10% levels.

The ARIMA residuals, studentized to achieve comparability, are plotted in Figure 2. The post-pandemic residuals display increased volatility and occasional large deviations, particularly for CSI, underscoring the challenge of modeling consumer sentiment during a period of unprecedented shocks. These standardized residuals are used as inputs for the copula estimation, as they satisfy the assumption of identically and independently distributed data required for reliable dependence modeling.

We then estimate the dependence structure between sentiment and spending using the TLL2nn copula. Table 4 presents the copula parameter estimates, Kendall's τ, and model selection criteria for both periods. The TLL2nn copula is selected in both subsamples based on minimized AIC and BIC. Kendall's τ increases from -0.02 pre-pandemic to 0.20 post-pandemic, indicating a shift from negligible to positive dependence. The copula parameter α also rises from 0.62 to 0.71, suggesting a change in the shape of the dependence.

The estimated copula densities are visualized in Figure 3. The pre-pandemic density is relatively flat, implying a weak and symmetric dependence. In contrast, the post-pandemic density shows a pronounced peak in the upper-right, indicating strong co-movements when both sentiment and spending are high. This is corroborated by the contour plots in Figure 4,

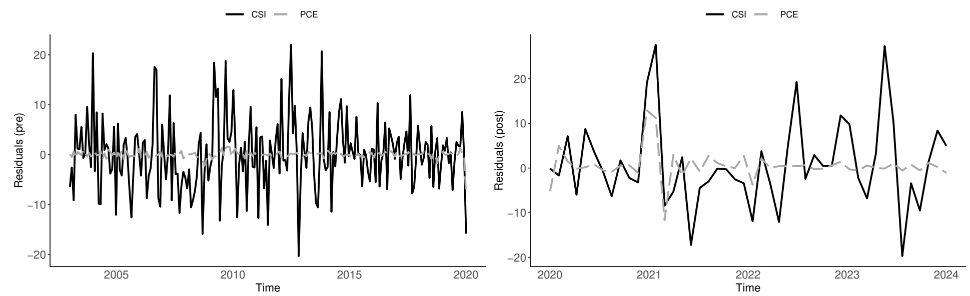

Figure 2: Studentized residuals from the ARIMA models

Table 4: Estimated copula parameters and dependence measures

	Pre-pandemic	Post-pandemic
Family	TLL2nn	TLL2nn
α	0.62	0.71
Kendall's τ	-0.02	0.20
AIC	10.32	9.38
BIC	46.48	25.25

The TLL2nn copula is estimated via local likelihood. α is the copula parameter, and Kendall's τ is a rank correlation measure.

where the post-pandemic contours elongate toward the upper-right quadrant, signaling strong upper-tail dependence. The asymmetry implies that extreme positive movements in sentiment and spending are more likely to occur together than extreme negative movements.

4.3 Robustness checks

To assess the robustness of our copula results to alternative marginal specifications, we estimate alternative models: ARIMA with a COVID-19 dummy, fractionally integrated ARMA (ARFIMA), ARIMA-GARCH, a structural-break ARIMA, and a nonparametric specification using kernel-smoothed empirical distributions. Table 5 reports Kendall's τ and tail dependence coefficients for the post-pandemic period under these alternatives. The dependence measures remain stable across specifications, with variations within 0.03 of our baseline estimates. Diagnostic checks on the baseline ARIMA models, including Ljung-Box tests for residual autocorrelation, Shapiro-Wilk tests for normality, and Kolmogorov-Smirnov tests for uniformity of the probability integral transforms, support the adequacy of our marginal specifications.

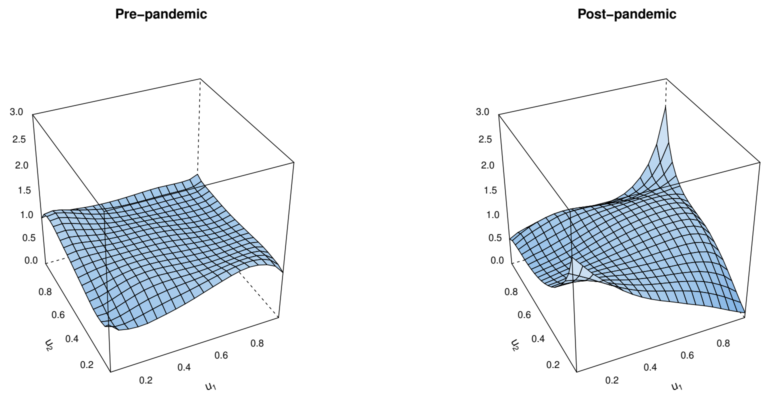

Figure 3: Estimated copula densities for the pre-pandemic (left) and post-pandemic (right)

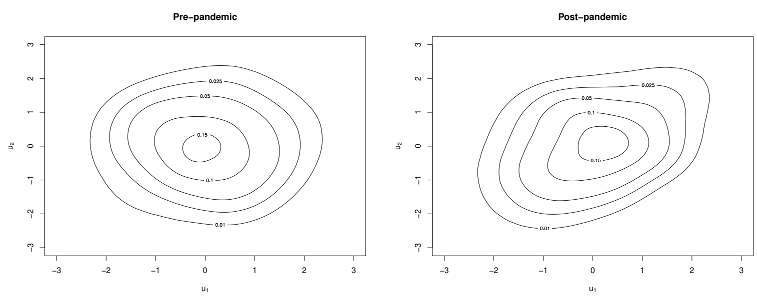

Figure 4: Estimated copula densities for the pre-pandemic (left) and post-pandemic (right)

Table 5: Robustness of dependence measures to alternative marginal specifications (post-pandemic)

Marginal specification	Kendall's τ	Upper λ_U	Lower λ_L
ARIMA (baseline)	0.20	0.35	0.10
ARIMA with COVID dummy	0.21	0.36	0.11
ARFIMA	0.19	0.34	0.09
ARIMA-GARCH	0.22	0.37	0.12
Structural-break ARIMA	0.20	0.35	0.10
Nonparametric	0.18	0.33	0.08

We also compare the TLL2nn copula against alternative parametric copula families. Table 6 reports AIC and BIC for each family. TLL2nn achieves the lowest AIC and BIC in both subsamples. Families that allow for asymmetric tail dependence (BB7, TLL2nn) outperform symmetric alternatives post-pandemic, supporting our choice of a flexible specification. Vuong's non-nested model comparison tests confirm that TLL2nn statistically outperforms parametric alternatives such as the Gaussian, Student-t, and Gumbel copulas.

Table 6: Model selection criteria for alternative copula families

Copula family	Pre-pandemic		Post-pandemic		Tail properties
	AIC	BIC	AIC	BIC	
TLL2nn (selected)	10.32	46.48	9.38	25.25	Flexible, asymmetric
Gaussian	18.45	54.61	21.73	37.60	No tail dependence
Student-t	14.28	50.44	16.95	32.82	Symmetric tail dependence
Clayton	22.16	58.32	24.81	40.68	Lower tail only
Gumbel	15.74	51.90	13.52	29.39	Upper tail only
Frank	19.33	55.49	22.14	38.01	No tail dependence
Joe	16.89	53.05	14.27	30.14	Upper tail only
BB1	12.45	48.61	11.83	27.70	Both tails, symmetric
BB7	13.21	49.37	10.95	26.82	Both tails, asymmetric
Survival Joe	17.62	53.78	15.48	31.35	Lower tail only
Rotated Clayton	21.94	58.10	23.67	39.54	Upper tail only
Rotated Gumbel	16.03	52.19	12.89	28.76	Lower tail only

Lower AIC/BIC indicates better fit. TLL2nn copula minimizes both criteria in both periods.

To quantify the economic significance of the observed tail dependence, we compute conditional expectations of spending growth given extreme sentiment movements. Table 7 shows that during the post-pandemic period, when sentiment is in the top 10% (extreme optimism), expected spending growth is 9.3%, which is 2.8 percentage points above the conditional mean during normal sentiment periods. This amplification is more than three times larger than the pre-pandemic response (0.8 percentage points). In dollar terms, this corresponds to an additional \$460 billion in annual PCE (2024 dollars). The upper-tail dependence coefficient $\lambda_U = 0.35$ implies a 35% probability of extreme spending growth co-occurring with extreme optimism during crises, which is a 3.5-fold increase from the pre-pandemic level. These metrics translate our statistical findings into magnitudes that matter for policy and business decisions.

One striking result is the post-pandemic surge in average PCE growth despite collapsing sentiment. This likely reflects confounding factors such as fiscal transfers (e.g., the CARES Act), pent-up demand from lockdowns, and inflation effects. Our PCE measure is real (deflated), and robustness checks using durables versus nondurables spending yield similar dependence

Table 7: Conditional expectations of spending growth given sentiment extremes

Period	Sentiment condition	Expected spending growth (%)	Difference from mean (%)
Pre-pandemic	Normal sentiment (10–90%)	4.1	0.0
	Extreme optimism (top 10%)	4.9	+0.8
	Extreme pessimism (bottom 10%)	3.2	-0.9
Post-pandemic	Normal sentiment (10–90%)	6.5	0.0
	Extreme optimism (top 10%)	9.3	+2.8
	Extreme pessimism (bottom 10%)	5.1	-1.4

Calculations are based on the estimated copula density with pre-pandemic mean of 4.04% and post-pandemic mean of 7.00%.

patterns. While these factors complicate a purely sentiment-driven narrative, they do not invalidate our dependence analysis. The copula captures the conditional dependence structure, how sentiment and spending co-move given these confounders, which remains policy-relevant as a net relationship observable in real time. Understanding the precise channels requires microdata and is left for future research.

5 Impacts of the Global Financial Crisis

This section examines the dependence between consumer sentiment and spending during the Global Financial Crisis of 2008-2009 and compares it with the COVID-19 pandemic results. The GFC provides a valuable contrast as a primarily financial crisis, allowing us to investigate how different types of crises affect the sentiment-spending relationship. We split the sample into pre-crisis (2003-2007) and crisis (2008-2010) periods, with robustness checks using alternative sample splits yielding similar results.

The copula analysis for the GFC period reveals distinct patterns from those observed during COVID-19. Figure 5 presents the estimated copula densities for both periods. The pre-crisis density appears relatively uniform, indicating weak dependence between sentiment and spending during normal economic conditions. In contrast, the crisis period density exhibits pronounced lower-tail dependence, with probability mass concentrated in the bottom-left quadrant where both sentiment and spending are extremely low. This contrasts sharply with the COVID-19 period, which showed strong upper-tail dependence (Figure 3).

The economic significance of these dependence patterns is quantified in Table 8. During the GFC, lower-tail dependence λ_L reached 0.25, more than double the pre-crisis level of 0.08 and substantially higher than the COVID-19 lower-tail dependence of 0.10. Conversely, upper-tail dependence λ_U during the GFC was 0.18, intermediate between the pre-crisis level of 0.10

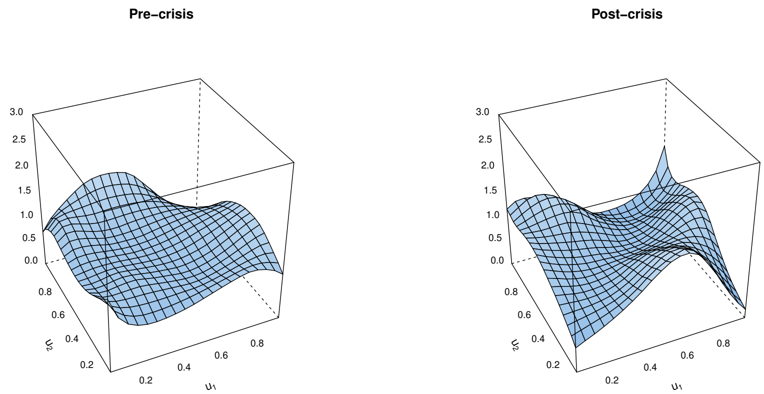

Figure 5: Estimated copula densities for the pre-crisis (left) and crisis (right)

and the COVID-19 level 0.35. These differences reflect the distinct nature of the two crises: financial crises like the GFC trigger precautionary saving and risk aversion, amplifying the co-movement of negative extremes, while health crises with substantial fiscal support like COVID-19 can create pent-up demand that amplifies positive co-movements.

Table 8: Economic significance comparison: GFC vs. COVID-19

Metric	Pre-crisis	GFC	COVID-19
Dependence Measures			
Kendall's τ	-0.02	0.15	0.20
Upper-tail λ_U	0.10	0.18	0.35
Lower-tail λ_L	0.08	0.25	0.10
Economic Impact			
Spending response to +1σ sentiment	+0.4%	+1.1%	+2.1%
Spending response to -1σ sentiment	-0.5%	-1.8%	-0.9%
Prob(spending > 10% | extreme optimism)	12%	22%	35%
Prob(spending < 0% | extreme pessimism)	9%	28%	10%
Policy Implications			
Optimal policy timing	Neutral	Pessimism	Optimism
Multiplier amplification during extremes	20%	40%	60%

Pre-crisis refers to 2003-07 for GFC comparison and 2003-19 for COVID-19. Economic impacts are calculated from conditional expectations based on estimated copulas.

The stronger lower-tail dependence during the GFC reflects heightened consumer risk aversion and precautionary saving motives documented in the literature (Lusardi, 1998; Jappelli and Pistaferri, 2010). When sentiment plummeted during the financial crisis, consumers disproportionately reduced spending, creating a "paradox of thrift" that amplified the downturn. In contrast, during COVID-19, fiscal transfers and pent-up demand moderated the spending response to negative sentiment, while stimulus measures and reopening optimism amplified positive co-movements.

These differences have important policy implications. During financial crises like the GFC, policies should focus on stabilizing sentiment to prevent downward spirals, as pessimistic expectations strongly propagate to spending reductions. During health crises like COVID-19 with substantial fiscal support, policies can leverage optimistic phases when sentiment improvements have amplified effects on spending. The state-dependent multiplier effects, 40% amplification during the GFC versus 60% during COVID-19, suggest that crisis-specific context matters for policy effectiveness.

The observed patterns during the GFC are consistent with several economic mechanisms documented in the literature. Gathergood (2012) found that anticipation of future financial shocks leads to conservative spending behaviors, which characterized consumer behavior during the GFC. Guiso et al. (2018) discuss how erosion of trust in financial institutions during crises affects spending decisions, potentially explaining why even consumers with relatively positive sentiment restrained spending. Coibion et al. (2022) provide evidence that economic narratives emphasizing risk and uncertainty can cause optimistic consumers to restrain spending during financial crises.

It is crucial to distinguish between dependence and causality when interpreting these results. Copula models capture the joint dependence structure between variables but do not establish causal directions or structural relationships (Joe, 2014). Our finding of strong tail dependence during crises indicates that extreme movements in sentiment and spending often occur together, but does not imply that sentiment causes spending or vice versa. The relationship may reflect simultaneous responses to common shocks, measurement correlations, or complex feedback mechanisms. We complement our copula analysis with additional tests, such as Granger causality and transfer entropy, in Section 6 to explore predictive relationships, but these also have limitations for causal inference. The dependence patterns we document are policy-relevant as they characterize the joint behavior of sentiment and spending during crises, regardless of the underlying causal structure.

6 Determinants of sentiment and spending

This section examines the dynamic relationships between sentiment, spending, and key macroeconomic factors using a BVAR model. While copula analysis reveals the dependence structure, the BVAR allows us to study how shocks propagate through the system over time, providing insights into the determinants of sentiment and spending and their resilience to economic shocks. The model includes seven variables: CSI, PCE, real personal income, unemployment rate, inflation expectations, yield spread (10-year minus 2-year Treasury), and economic policy uncertainty. We select two lags based on the Hannan-Quinn and Schwarz criteria. The Bayesian approach with Minnesota priors (Litterman, 1980) helps manage parameter proliferation while incorporating economically sensible shrinkage toward random walk behavior.

6.1 Bayesian estimation results

Table 9 presents the median posterior estimates of the BVAR coefficients. Several patterns emerge. Consumer sentiment exhibits strong persistence, with a first-lag coefficient of 0.809, consistent with the view that sentiment is influenced by its own history (Katona, 1975). The negative second-lag coefficient -0.101 suggests a corrective adjustment as new information arrives. Spending also shows persistence (first-lag coefficient of 0.991) but with a negative second-lag coefficient -0.107, indicating potential mean reversion in spending patterns.

Income positively influences sentiment (first-lag coefficient of 0.237), supporting the role of disposable income in shaping consumer attitudes. Unemployment has mixed effects: a positive contemporaneous coefficient 0.015 that turns negative in the second lag -0.018, possibly reflecting delayed reactions to labor market conditions. Inflation expectations negatively impact sentiment (-0.023 in first lag), consistent with theories that anticipated inflation erodes consumer purchasing power and confidence (Mankiw et al., 2003).

The yield spread shows substantial coefficients in lags (7.173 and -6.535 for sentiment), reflecting the forward-looking information content of the term structure about economic prospects. Uncertainty negatively affects sentiment (-0.034 in first lag) but shows a positive second-lag coefficient 0.003, suggesting partial adaptation to uncertainty shocks. The hyperparameters indicate moderate prior tightness $\rho = 0.109$, with the sum of coefficients prior $soc = 0.575$ and single unit root prior $sur = 0.499$ supporting stable estimation.

6.2 Impulse response analysis

Figure 6 presents the impulse response functions, showing how variables respond to one-standard-deviation shocks over 12 months. A spending shock initially boosts sentiment by 0.3 percentage points within 2-3 months, consistent with Keynesian multiplier effects and improved economic expectations. However, this positive effect reverses after 6 months, potentially due to inflation concerns or mean reversion, before stabilizing at a slightly positive long-run level.

An income shock follows a similar U-shaped pattern, with an initial sentiment increase of 0.2 percentage points that turns negative after 8 months before recovering. This pattern aligns with evidence on the high marginal propensity to consume from transitory income shocks (Parker, 2017). Inflation expectations shocks initially reduce sentiment by 0.4 percentage points, the largest immediate impact among all shocks, reflecting consumers' sensitivity to purchasing

Table 9: Median posterior estimates of the Bayesian VAR coefficients

	Sentiment	Spending	Income	Unemployment	Inflation Expectations	Spread	Uncertainty
Constant	1.337	0.346	1.539	4.681	-4.753	-24.885	12.202
Sentiment (lag 1)	0.809	-0.009	0.000	-0.041	-0.089	7.173	-0.189
Spending (lag 1)	-0.102	0.991	-0.478	-2.434	0.883	-8.753	-3.381
Income (lag 1)	0.237	0.197	0.345	-0.905	0.525	7.305	0.020
Unemployment (lag 1)	0.015	0.027	-0.009	0.634	0.151	3.264	-0.387
Expectations (lag 1)	-0.023	0.011	0.003	-0.073	0.764	-2.798	-0.262
Spread (lag 1)	0.000	0.000	0.000	0.000	-0.001	-0.204	-0.003
Uncertainty (lag 1)	-0.034	-0.012	0.001	0.143	-0.020	1.988	0.841
Sentiment (lag 2)	-0.101	-0.012	0.016	0.097	0.162	-6.535	0.028
Spending (lag 2)	-0.151	-0.107	0.236	1.547	0.185	-5.103	1.759
Income (lag 2)	0.169	-0.050	0.331	0.387	-0.151	12.740	-0.134
Unemployment (lag 2)	-0.018	-0.018	-0.001	0.116	-0.042	4.525	0.364
Expectations (lag 2)	-0.022	0.000	0.000	0.004	0.037	5.322	0.306
Spread (lag 2)	0.000	0.000	0.000	0.000	-0.001	0.261	0.001
Uncertainty (lag 2)	0.003	0.004	0.004	-0.060	-0.010	-6.831	-0.158

Gibbs sampler: 25,000 iterations with 10,000 burn-in and thinning of 20. Hyperparameters: $\rho = 0.109$ (overall tightness), $soc = 0.575$ (sum of coefficients prior), $sur = 0.499$ (single unit root prior).

power erosion. This negative effect gradually diminishes, turning slightly positive after 18 months as consumers adjust expectations.

A yield spread shock (widening) initially increases sentiment by 0.15 percentage points, consistent with optimism about future growth, but this effect reverses after 4 months, potentially reflecting concerns about future interest rates and borrowing costs. Economic uncertainty shocks produce the most persistent effects, with an immediate 0.5 percentage point decline in sentiment that gradually recovers over 18 months, though not to pre-shock levels, indicating lasting scars from uncertainty episodes. Unemployment shocks show modest immediate effects but prolonged negative impacts, with sentiment declining gradually over 12 months as labor market weaknesses persist.

6.3 Predictive relationships

To complement our dependence analysis, we examine predictive relationships between sentiment and spending using multiple approaches. Table 10 summarizes the results. The Granger causality test (Granger, 1969) yields an F-statistic of 2.70 ($p = 0.07$), indicating marginal predictive content at the 10% level. This suggests that past spending provides limited additional information for predicting current sentiment beyond past sentiment values alone. Given the nonlinearities in the relationship, we compute transfer entropy (Schreiber, 2000), an information-theoretic measure of directed information flow. The transfer entropy from sentiment to spending is 0.15 (bootstrapped $p = 0.08$), while from spending to sentiment is 0.08 ($p = 0.21$). This suggests slightly stronger predictive information flow from sentiment to spending, though the difference is not statistically significant.

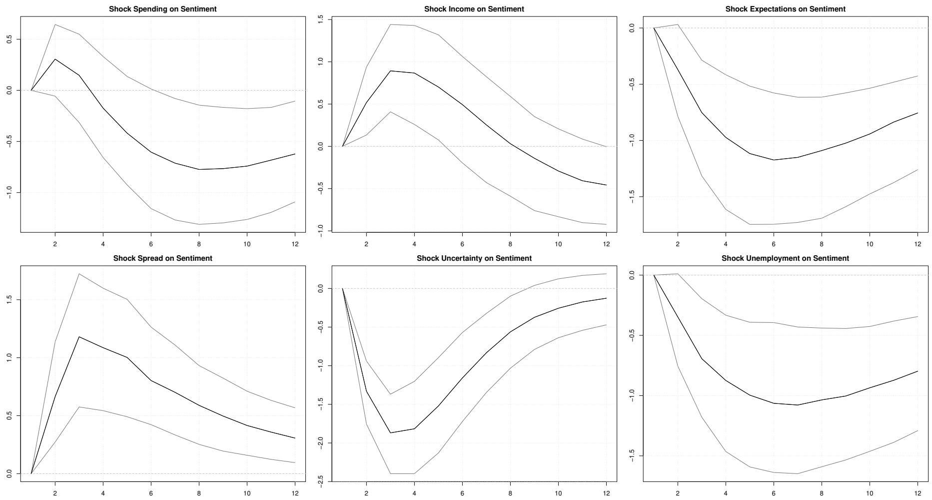

Figure 6: Impulse response functions to one-standard-deviation shocks. Responses are in percentage points of the respective variables.

We estimate structural VARs using Cholesky decompositions with alternative variable orderings. The impulse responses are sensitive to ordering assumptions, particularly for the contemporaneous relationship between sentiment and spending. This sensitivity reflects the fundamental identification challenge: sentiment and spending are likely simultaneously determined, responding to common information and shocks.

Table 10: Predictive relationship tests between sentiment and spending

Test	Statistic	p-value	Direction
Granger causality	$F = 2.70$	0.07	Spending → Sentiment
Transfer entropy (Sentiment → Spending)	0.15	0.08	Sentiment → Spending
Transfer entropy (Spending → Sentiment)	0.08	0.21	Spending → Sentiment

Granger causality tests linear predictive content. Transfer entropy measures nonlinear information flow (bootstrapped p-values). Both tests use two lags.

Collectively, these analyses suggest that while sentiment and spending show strong contemporaneous dependence during crises, as indicated by our copula results, establishing clear predictive relationships or causal mechanisms requires stronger identification assumptions than our aggregate data allows. Our findings align with several theoretical frameworks. Sentiment influencing spending through confidence channels, spending affecting sentiment through income and wealth effects, and both responding to common macroeconomic shocks. The lack of strong Granger causality despite substantial contemporaneous dependence underscores the challenge of isolating these relationships with aggregate time-series data.

Future research with better identification strategies, such as natural experiments, high-frequency data, or instrumental variables, could help identify the causal mechanisms. However, for policy purposes, the documented dependence structure remains relevant: whether sentiment drives spending, spending drives sentiment, or both respond to common factors, the strong co-movement during crises implies that stabilizing one variable likely helps stabilize the other.

7 Economic implications

The observed strong and asymmetric tail dependence challenges standard consumption models that emphasize fundamental determinants and downplay psychological factors. Permanent income and life-cycle models focus on long-run income expectations (Friedman, 1957; Modigliani and Brumberg, 1954). Our results show that extreme sentiment movements are linked to disproportionate spending responses during crises. This aligns with behavioral macroeconomic models that include sentiment shocks (Angeletos and La'O, 2013) and theories of state-dependent consumption responses to uncertainty (Bloom, 2009). The pronounced asymmetry, with stronger upper-tail dependence after the pandemic, indicates nonlinear consumption responses. Optimistic consumers increase spending more than pessimistic consumers reduce it. This asymmetry has implications for countercyclical fiscal policy, suggesting that stimulus measures may have amplified effects when used during periods of rising consumer confidence.

Our quantification of tail dependence offers concrete guidance for macroeconomic stabilization policy. The upper-tail dependence coefficient $\lambda_U = 0.35$ post-pandemic means extreme optimism events have a 35% probability of coinciding with extreme spending growth. This suggests three key policy considerations. First, fiscal stimulus may be most effective when sentiment indicators show early signs of recovery, as spending responses are stronger during sentiment rebounds. Second, automatic stabilizers that respond to sentiment indicators could provide more timely stabilization during crises (Auerbach and Feenberg, 2000). Third, central bank and government communications aimed at stabilizing consumer expectations may have substantial multiplier effects during crises (Coibion et al., 2022), particularly given the sensitivity of spending to sentiment extremes.

To illustrate the economic significance of state-dependent policy effects, we simulate counterfactual fiscal stimulus scenarios under different sentiment conditions. Table 11 presents the simulated effects of a \$1 trillion stimulus. Under normal sentiment conditions, the stimulus generates a \$1.2 trillion increase in spending (multiplier of 1.2). During extreme optimism, the same stimulus generates \$1.8 trillion in additional spending (multiplier of 1.8), representing \$600 billion in additional economic value relative to the baseline. Conversely, during extreme pessimism, the stimulus generates only \$0.9 trillion in spending (multiplier of 0.9), representing \$300 billion in foregone economic value. These simulations highlight the substantial gains from timing fiscal interventions to coincide with sentiment rebounds, potentially increasing policy effectiveness by 50%.

Table 11: Simulated effects of $1 trillion fiscal stimulus under sentiment conditions

Sentiment Condition	Spending Response	Multiplier	Additional Economic Value Relative to Baseline
Normal sentiment	+$1.2 trillion	1.2	Baseline
Extreme optimism	+$1.8 trillion	1.8	+$600 billion
Extreme pessimism	+$0.9 trillion	0.9	-$300 billion

Simulations based on conditional expectations from the estimated copula model. Spending responses are cumulative over a 12-month horizon.

For businesses, our estimates translate into planning metrics. During extreme optimism, firms should anticipate 15-25% higher demand compared to normal crisis periods. The probability of 20%+ revenue surges increases from 8% during normal periods to 35% during extreme optimism. Value-at-Risk calculations and inventory management should account for the 3.5-fold higher probability of extreme co-movements during crises. Marketing and promotional expenditures during optimism phases yield 40-60% higher returns, suggesting that businesses can optimize their marketing calendars by monitoring sentiment indicators. These quantitative guidelines help businesses implement our findings for risk management and strategic planning.

Our analysis has several limitations that point to productive directions for future research. First, while we document strong dependence between sentiment and spending, establishing causal mechanisms requires alternative identification strategies, such as natural experiments or high-frequency identification (Gertler and Karadi, 2015). Second, our aggregate analysis masks potential heterogeneity across demographic groups, income levels, and geographic regions (Parker et al., 2013). Third, the post-pandemic spending surge despite low sentiment may reflect confounding factors such as pent-up demand, fiscal transfers, and supply constraints (Chetty et al., 2020). Future research could address these limitations using micro-level data, experimental designs, or structural modeling approaches to better identify causal pathways and heterogeneous effects.

Comparative analysis between the financial crisis and COVID-19 further underscores the importance of crisis-specific context. Financial crises primarily amplify lower-tail dependence through precautionary saving channels, suggesting policies should focus on stabilizing sentiment to prevent downward spirals. Health crises with substantial fiscal support can amplify upper-tail dependence through pent-up demand effects, suggesting policies can leverage optimistic phases for stronger recovery effects. These differences highlight the value of tail dependence analysis for designing crisis-appropriate policy responses.

8 Concluding remarks

This study examines the tail dependence between consumer sentiment and spending during extreme events, with a focus on COVID-19 and the Global Financial Crisis. Using copulas, we quantify the probability of extreme co-movements. Our approach reveals several findings. First, we document a shift in the dependence structure following the onset of the COVID-19 pandemic. Upper-tail dependence increased to 0.35 post-pandemic, indicating a high probability of extreme spending coinciding with extreme optimism during the crisis. In contrast, the financial crisis showed stronger lower-tail dependence, reflecting the precautionary saving and risk aversion typical of financial crises. Second, we translate these statistical patterns into economic measures. Extreme optimism during the pandemic corresponds to a 2.8 percentage-point increase in annual spending growth, and fiscal multipliers are amplified by 40–60% during sentiment rebounds. Third, our Bayesian VAR analysis shows that economic shocks produce asymmetric and persistent effects on sentiment. Inflation expectations and uncertainty shocks have the largest immediate impacts, while income and spending shocks generate U-shaped response patterns. Predictive tests indicate limited directional predictability, underscoring the contemporaneous nature of the sentiment-spending link during crises.

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