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Volatility Spillovers in Macao's Gaming Economy before and after COVID-19

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ABSTRACT

Risk analyses of Macao's gaming-tourism economy have long rested on two implicit assumptions: that the co-movement between overnight visitor arrivals and gaming revenue is positive and stable, and that adverse shocks propagate no more severely than favourable ones. Using monthly data from February 2008 to July 2025 and a framework combining GJR-GARCH, Dynamic Conditional Correlation, and the Diebold-Yilmaz spillover decomposition, this paper tests both assumptions and finds that neither survives empirical scrutiny. The dynamic correlation between overnight arrivals and gaming revenue was positive and stable before 2020, effectively collapsed during the COVID-19 border closure, and has remained persistently negative since 2022, a reversal that has not self-corrected in three years of post-pandemic recovery. Separately, the spillover of bad volatility shocks between the two series is 30.6 percent, against 8.2 percent for good volatility shocks, a gap of 22.4 percentage points. Together, these results describe a gaming-tourism system in which the standard assumptions of stability and symmetry both fail simultaneously, and in which any risk model calibrated on pre-2020 data or symmetric shock mechanics will understate downside exposure by a structurally significant margin.

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1. Introduction

Few places in the global tourism economy present as concentrated a risk profile as Macao. Gaming tax provides roughly 78 percent of government revenue (Lim and To, 2022), drawn almost entirely from a single source market: Mainland China. The two most closely monitored monthly indicators, visitor arrivals and gaming tax revenue, are structurally coupled: over 70 percent of the monthly variation in gaming revenue is explained by changes in visitor arrivals alone (Lim and To, 2022). Yet within the aggregate arrival figure lies a distinction that carries substantial economic weight. Overnight visitors generate a disproportionate share of casino spending relative to same-day visitors. Masiero, Qian, Fong and Law (2018) document that same-day visitors who gambled in Macao spent an average of US$80 per capita, compared with US$437 for overnight visitors, a ratio of more than five to one. Overnight visitors book hotels, revisit casinos multiple times during their stay, and engage more deeply with the full range of hospitality services. It follows that the volatility of overnight visitor arrivals should be the more informative signal for gaming revenue uncertainty than total visitor counts, which are diluted by the large share of same-day traffic.

The literature on tourism demand modelling is extensive, as surveyed by Song and Li (2008), but two gaps are relevant here. The first concerns stability. Existing studies of tourism volatility typically estimate GARCH specifications on individual arrival series and treat their parameters as constant across the full sample (Shareef and McAleer, 2007; Chan, Lim and McAleer, 2005). The implicit assumption is that the structural relationship between demand indicators and revenue outcomes does not change over time. The COVID-19 pandemic, and the institutional reforms that accompanied it in Macao, provide a natural test of that assumption. The second concerns symmetry. The leverage effect literature shows that within a single tourism series, negative shocks tend to generate more subsequent volatility than positive shocks of equal magnitude (Balli, Tsui and Balli, 2019; Kim and Wong, 2006). Whether this asymmetry extends to cross-series transmission, so that bad news in overnight arrivals generates more volatility in gaming revenue than good news of the same size, has not been examined. Rastogi and Kanoujiya (2023) apply bivariate DCC-GARCH to inbound tourism and macroeconomic indicators in India, and Tang (2025) examines how aggregate uncertainty affects Macao's gaming revenue using a vector autoregression, but neither study addresses the stability or symmetry of the overnight arrival-gaming revenue relationship specifically.

This paper tests both assumptions simultaneously using monthly data from February 2008 to July 2025. We apply the GJR-GARCH model to characterise the conditional variance of overnight visitor arrivals and gaming revenue separately, the DCC-GARCH model of Engle (2002) to estimate whether their co-movement is stable or time-varying, and the Diebold-Yilmaz (2009, 2012) spillover framework to measure directional risk transmission and its asymmetry across positive and negative shocks. Two research questions follow directly. First, does the dynamic correlation between overnight visitor arrivals and gaming revenue remain stable across the pre-COVID, COVID, and post-COVID periods? Second, does the cross-series transmission of bad volatility shocks differ in magnitude from the transmission of good volatility shocks? Section 2 presents data and methods. Section 3 reports results. Section 4 discusses the implications. Section 5 concludes.

2. Methodology

2.1. Data

Monthly overnight visitor arrivals, measured in persons, and gaming tax revenue paid to public accounts, measured in millions of Macao Patacas (MOP), are sourced from the Statistics and Census Service of Macao (DSEC). Both series cover February 2008 to July 2025, yielding 209 log-return observations after first differencing. Overnight visitors are defined as inbound arrivals who stay at least one night; same-day visitors and overnight visitors together sum exactly to total arrivals. The overnight share averages 47.1 percent over the sample, ranging from 42.5 percent during the COVID-19 border closure to 53.0 percent in 2016 to 2018. The training sample ends in December 2021; the hold-out test sample runs from January 2022 to July 2025. Table 1 defines all symbols used in the analysis.

Table 1. Notation and Variable Definitions

Symbol	Definition
r_t	Monthly log-return of a series, computed as $100 \times \ln(Y_t / Y_{t-1})$
Y_t	Level of overnight visitor arrivals (persons) or gaming tax revenue (MOP millions)
ε_t	Mean-equation innovation; $\varepsilon_t = h_t^{1/2} z_t$
h_t	Conditional variance from the GJR-GARCH model
z_t	Standardised innovation; $z_t = \varepsilon_t / h_t^{1/2} \sim N(0, 1)$
I_{t-1}	Indicator variable; equals 1 if $\varepsilon_{t-1} < 0$, and zero otherwise
$\omega, \alpha, \gamma, \beta$	GJR-GARCH variance parameters: intercept, ARCH, asymmetry, GARCH
Q_t	DCC auxiliary positive-definite matrix
$\bar{Q}$	Unconditional correlation matrix of standardised residuals

R_t	Time-varying conditional correlation matrix; $R_t = \text{diag}(Q_t)^{-½} Q_t \text{diag}(Q_t)^{-½}$
ϱ_t	Off-diagonal element of R_t: the dynamic conditional correlation at time t
a, b	DCC parameters: speed of correlation adjustment and persistence (a + b < 1)
θ^{ij}	Generalised FEVD element: fraction of series i's forecast error variance due to series j
TSI	Total Spillover Index: average cross-market contribution to forecast error variance
D_COVID	Structural break dummy: equals 1 from February 2020 to December 2022
D_REOPEN	Structural break dummy: equals 1 from January to June 2023
D_GFC	Structural break dummy: equals 1 from October 2008 to June 2009

2.2. Preliminary Tests

Stationarity is assessed with the Augmented Dickey-Fuller (ADF) test, with lag length selected by the Akaike Information Criterion, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). Level series are I(1); log-returns are I(0). ARCH effects are tested via the Engle (1982) Lagrange Multiplier test and the Ljung-Box Q-statistic applied to squared residuals of an AR(1) mean equation at twelve lags.

2.3. GJR-GARCH Model

The GJR-GARCH(1,1) model of Glosten, Jagannathan and Runkle (1993) is estimated for each series. The mean equation is:

$$r_t = \mu + \varphi r_{t-1} + \delta_1 \text{D\_COVID} + \delta_2 \text{D\_REOPEN} + \varepsilon_t \quad (1)$$

The variance equation is:

$$h_t = \omega + (\alpha + \gamma I_{t-1})\varepsilon^2_{t-1} + \beta h_{t-1} \quad (2)$$

where $I_{t-1} = 1$ when $\varepsilon_{t-1} < 0$, and zero otherwise. A positive γ confirms that negative shocks generate disproportionately large increases in conditional variance, constituting the leverage effect. The stationarity condition is $\alpha + \gamma/2 + \beta < 1$. Both models are estimated by maximum likelihood using the BFGS algorithm. Standardised residuals $z_t = \varepsilon_t / h_t^{½}$ from this step feed directly into the DCC model.

2.4. DCC-GARCH Model

The Dynamic Conditional Correlation model of Engle (2002) estimates time-varying correlations in a two-step procedure. Step one produces the standardised residuals z_t from the univariate GJR-GARCH models. Step two specifies the dynamics of the auxiliary matrix Q_t:

$$Q_t = (1 - a - b)\bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1} \quad (3)$$

where $\bar{Q}$ is the unconditional correlation matrix of standardised residuals, and a and b are scalar parameters satisfying a, b > 0 and a + b < 1. The conditional correlation matrix is then $R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \mathrm{diag}(Q_t)^{-1/2}$. The off-diagonal element ϱ_t of R_t is the time-varying conditional correlation coefficient. Rastogi and Kanoujiya (2023) demonstrate the applicability of bivariate DCC-GARCH to inbound tourism series, confirming that the model captures meaningful time-varying dynamics in non-financial arrival data.

2.5. Diebold-Yilmaz Spillover Framework

The Diebold and Yilmaz (2009, 2012) framework uses a Vector Autoregression estimated on the conditional volatility series and decomposes its forecast error variance to quantify directional risk transmission. The generalised forecast error variance decomposition (GFEVD) of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) is order-invariant. The element θ^{Ij} gives the fraction of series i's H-step-ahead forecast error variance attributable to shocks from series j. The Total Spillover Index is:

$$TSI = 100 \times \sum_{i \neq j} \theta^{\eta j} / \mathrm{k} \quad (4)$$

Net directional spillovers are computed as the difference between what each series transmits to others and what it receives. To address the third research question, we separately estimate the spillover framework using bad volatility, the component of conditional variance attributable to negative shocks, and good volatility, the component from positive shocks, following Barunik, Kocenda and Vacha (2017). A rolling 60-month window estimates of the Total Spillover Index track how risk integration evolves over time. All estimations use VAR order p = 2 and forecast horizon H = 10.

3. Results

3.1. Descriptive Statistics and Preliminary Tests

The distributional properties of the two series immediately signal the kind of risk environment this paper models. Both log-return series are heavily left-skewed and leptokurtic: overnight visitors carry excess kurtosis of 35.43 and skewness of -1.27, reflecting the once-in-a-generation collapse of 2020, while gaming revenue shows excess kurtosis of 15.15 and skewness of -1.53. These fat left tails are not statistical curiosities; they correspond to real events where border closures and regulatory decisions drove arrivals and revenue to near-zero within weeks. Table 2 formalises these properties. The Jarque-Bera test rejects normality for both series at the one percent level, and ARCH-LM statistics of 37.0 and 34.4 confirm that volatility in both markets is time-varying and predictable from its own past, the empirical condition that makes GARCH modelling both valid and necessary. Figure 1 makes the scale of the COVID-19 disruption concrete: the log-return bars for 2020 are so large they compress the visual variation of every other episode in the sample.

Table 2. Descriptive Statistics of Log-Return Series (February 2008 to July 2025)

Series	N	Mean	Std Dev	Min	Max	Skewness	Kurtosis (excess)
Overnight visitors (%)	209	0.23	56.40	-425.3	423.6	-1.27	35.43
Gaming revenue (%)	209	0.35	29.44	-190.2	132.3	-1.53	15.15

The overnight visitor share shown in panel (a) of Figure 1 holds remarkably steady at around 47 percent for most of the sample, a structural regularity that makes the post-2022 decline toward 41 to 42 percent noteworthy: returning visitors after COVID-19 tended to make shorter trips, which is one reason the gaming-tourism correlation changed sign in the recovery period.

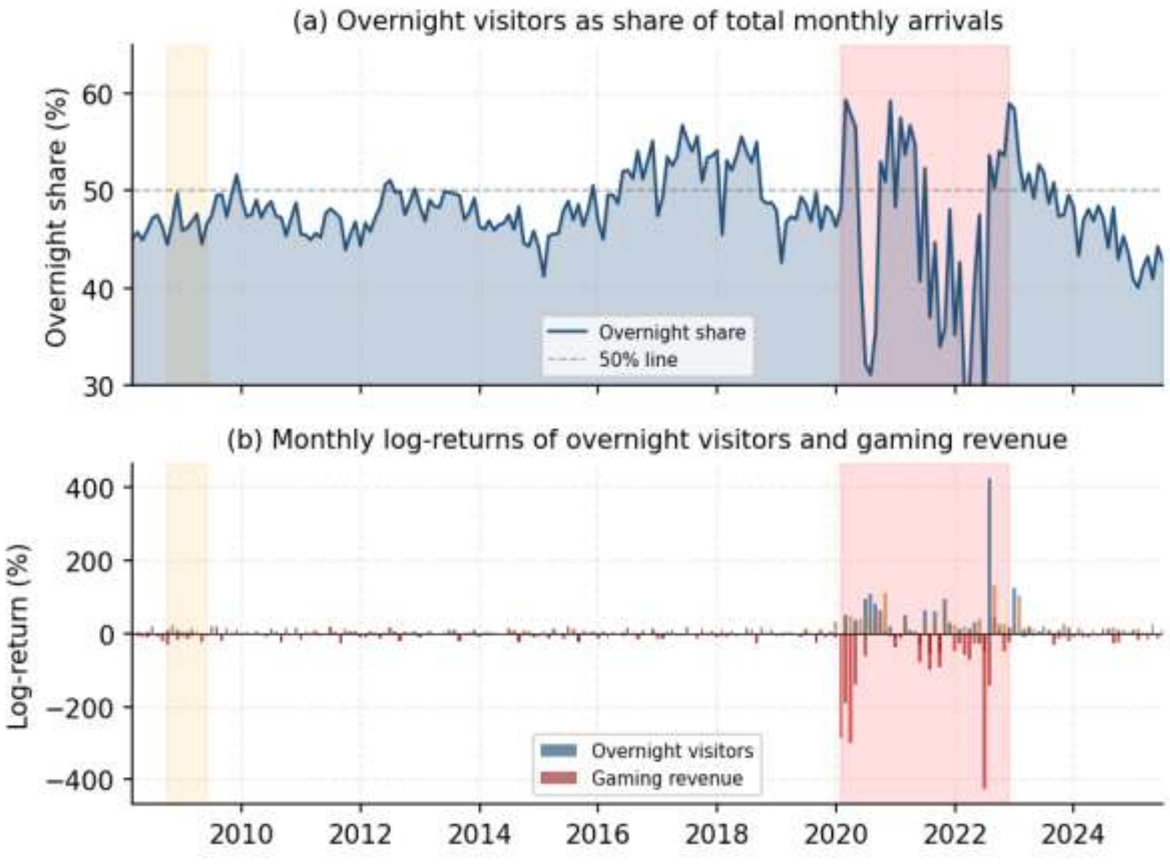


Figure 1. Overnight visitor share and log-returns, February 2008 to July 2025. Orange shading: GFC. Red shading: COVID-19 border closure.

3.2. GJR-GARCH Model Estimates

Table 3 reports the GJR-GARCH parameter estimates. Both series exhibit a positive and statistically meaningful asymmetry coefficient γ. For overnight visitors, γ = 0.178 implies that a negative arrival shock generates approximately 24 percent more conditional variance in the following period than an equivalent positive shock. For gaming revenue, γ = 0.294 is larger, indicating that negative gaming shocks are particularly destabilising for the series' own variance. Persistence is 0.910 for overnight visitors and 0.853 for gaming revenue, both below unity as required for covariance stationarity. Figure 2 plots the estimated conditional standard deviations, confirming that the COVID-19 peak dwarfs all prior episodes by a substantial margin.

Table 3. GJR-GARCH(1,1) Parameter Estimates

Series	ω	α	γ	β	Persistence	AIC
Overnight visitors	158.29	0.1866	0.1779	0.7232	0.9098	1744.1
Gaming revenue	43.07	0.3779	0.2935	0.4747	0.8526	1455.9

Persistence = α + β. Mean equation includes AR(1) term and binary dummies for COVID-19, reopening, and GFC. Estimation by BFGS maximum likelihood.

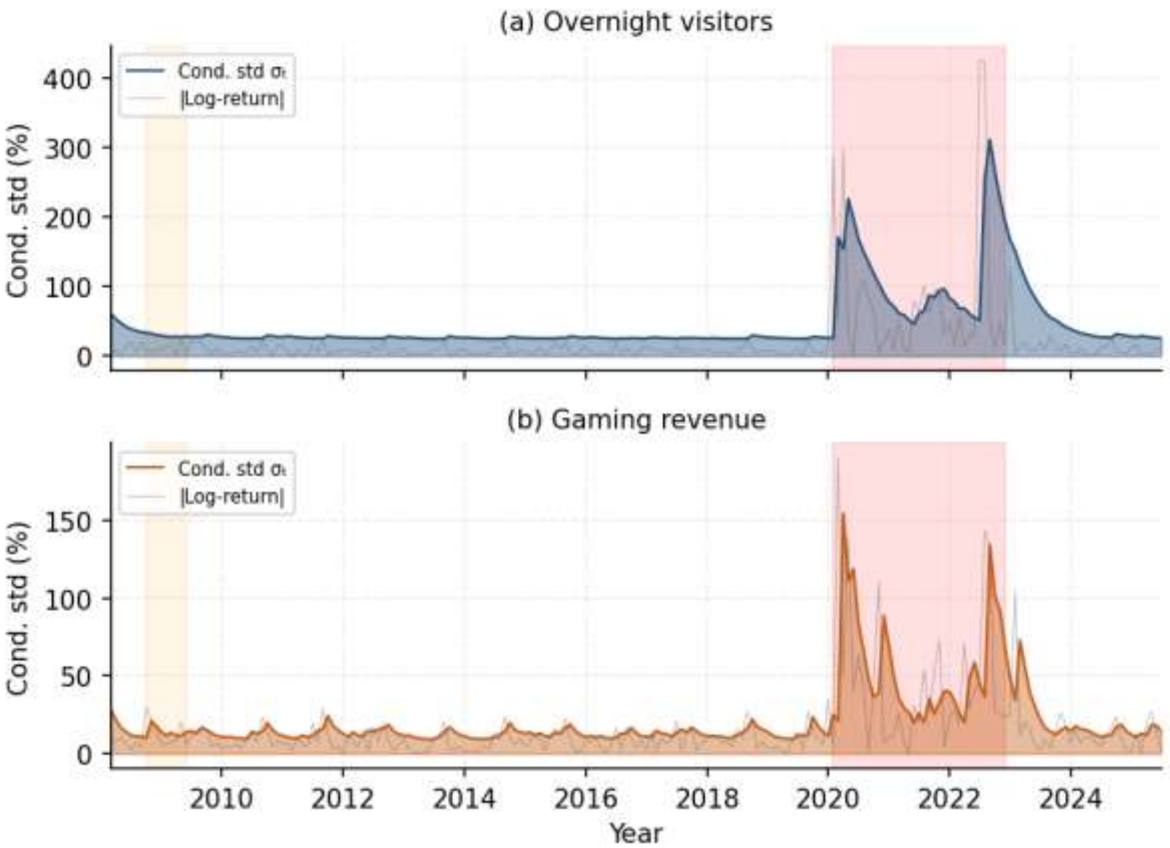


Figure 2. Estimated conditional standard deviation from GJR-GARCH models. Panel (a): overnight visitors. Panel (b): gaming revenue. Orange shading: GFC. Red shading: COVID-19.

3.3. Dynamic Conditional Correlation

The DCC model directly tests the first assumption: that the co-movement between overnight arrivals and gaming revenue is positive and stable. Table 4 and Figure 3 show it is neither. Before COVID-19, the mean correlation of 0.160 reflects the expected positive relationship and is consistent with a stable, slowly adjusting system, as indicated by the DCC persistence parameter b = 0.900. The COVID-19 border closure drove both series simultaneously to near-zero levels, reducing their measured correlation to essentially zero (0.009), which is the expected result when a common external shock dominates both series. The critical finding is what happens after the border reopens. The post-2022 mean correlation of -0.071 is negative, and Figure 3 shows that this sign reversal is not transient: the DCC estimate crosses below zero around mid-2022 and remains there for the remainder of the three-year post-pandemic observation window. A correlation that was positive and stable for twelve years has not reverted to its historical level even after visitor arrivals recovered to near pre-pandemic volumes. The stability assumption, which the pre-2020 data would not have challenged, fails when evaluated over the full sample.

Table 4. DCC-GARCH Results: Time-Varying Correlation Summary

Period	Mean ϱ_t	Min ϱ_t	Max ϱ_t	DCC a	DCC b
Full sample (2008–02 to 2025–07)	0.100	-0.145	0.257	0.050	0.900
Pre-COVID (before 2020-02)	0.160	0.003	0.257		
COVID-19 (2020-02 to 2022-12)	0.009	-0.145	0.107		
Post-COVID (after 2022-12)	-0.071	-0.145	0.084		

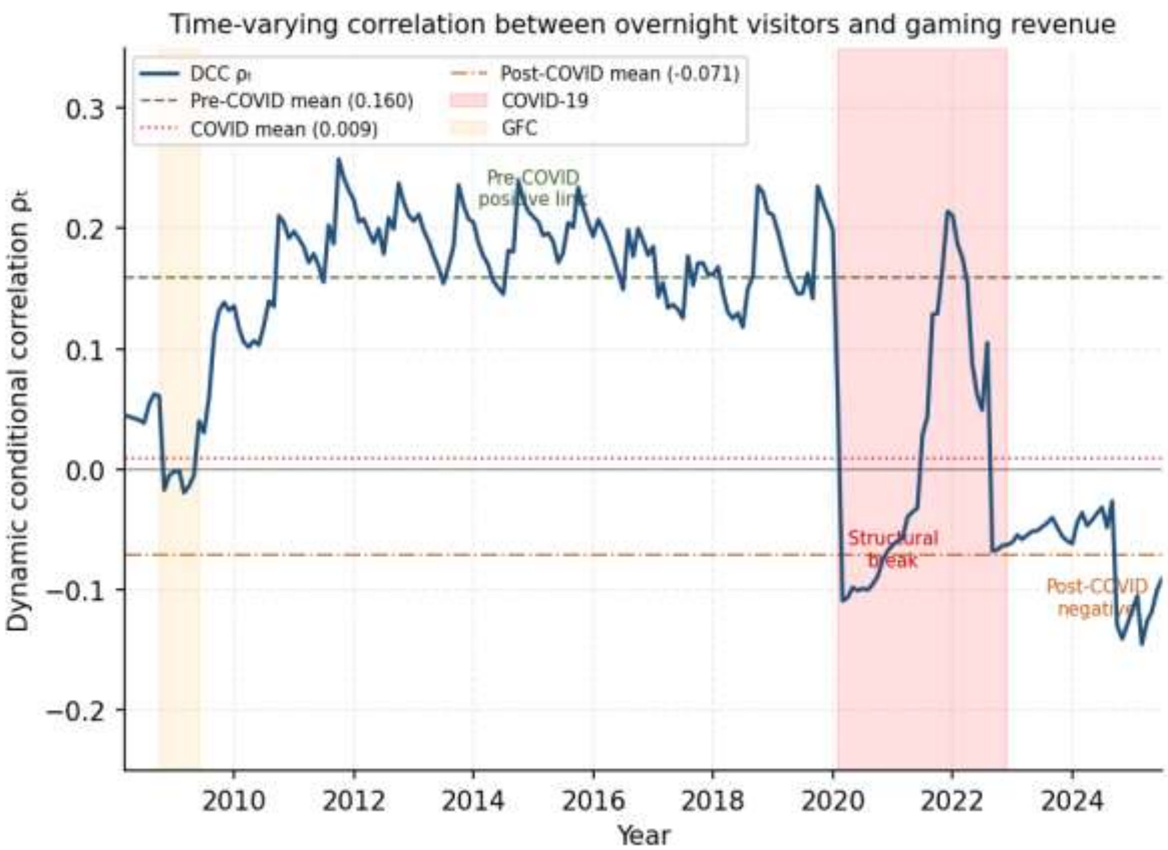


Figure 3. Time-varying DCC correlation between overnight visitor arrivals and gaming revenue. Horizontal dashed lines mark sub-period means. Orange shading: GFC. Red shading: COVID-19.

3.4. Diebold-Yilmaz Spillover Results

With the correlation structure characterised, the Diebold-Yilmaz framework decomposes directional risk transmission from conditional volatility series. The full-sample Total Spillover Index of 41.4 percent confirms that cross-series shocks account for a substantial share of forecast error variance in this system. The directional breakdown in Table 5, where overnight arrival shocks explain 64.0 percent of gaming revenue's forecast error variance while gaming shocks explain only 18.7 percent of arrival variance, is consistent with the known causal structure: visitors must arrive before revenue is generated, so demand-side uncertainty precedes supply-side uncertainty in the data. This directional pattern validates the model's behaviour against prior expectations before the asymmetric decomposition is applied.

Table 5. Diebold-Yilmaz Volatility Spillover Table (VAR order 2, horizon H = 10)

From / To	Overnight visitors (%)	Gaming revenue (%)	From others (%)
Overnight visitors	81.3	18.7	18.7
Gaming revenue	64.0	36.0	64.0

To others (%)	64.0	18.7	TSI = 41.4%
Net (%)	+45.3	-45.3	

Entries show the percentage of forecast error variance of the row series attributable to shocks from the column series. TSI: Total Spillover Index. Net = To others minus From others. Rows sum to 100 before rounding.

The static spillover table captures the full-sample average but conceals the evolution of risk integration over time. Figure 4 tracks this evolution through a rolling 60-month window estimate. Several features stand out. Integration between the two markets was broadly rising in the years before 2020, reaching above 45 percent, consistent with the deepening structural link between overnight visitor demand and casino revenue as Macao's gaming industry matured. COVID-19 caused a sharp decline in the rolling index, not because the markets were less connected in some economic sense, but because both were simultaneously suppressed by the same external shock, leaving little variance to decompose directionally. The partial recovery post-2022 that stabilises below the pre-pandemic peak is consistent with the correlation sign reversal documented by the DCC model: risk integration has resumed, but through a structurally different mechanism than before.

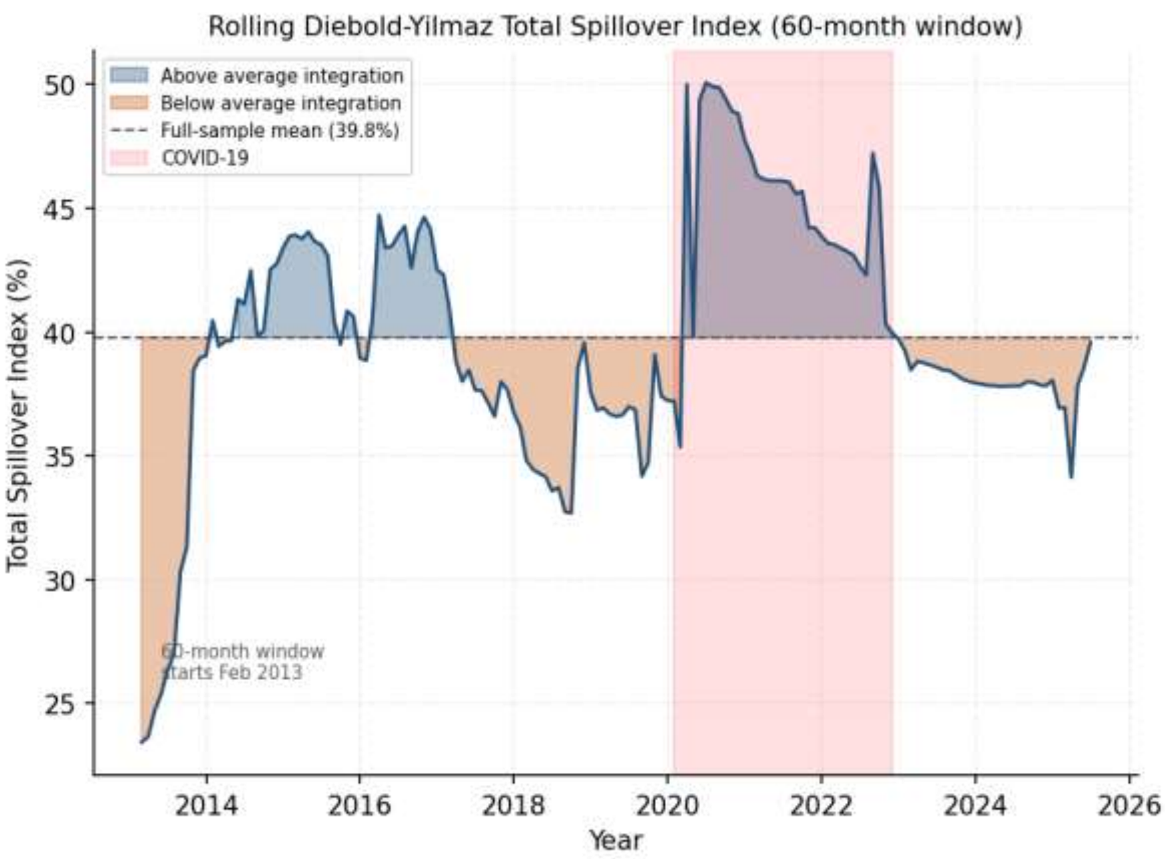


Figure 4. Rolling Diebold-Yilmaz Total Spillover Index (60-month window). Dashed line: full-sample mean. Note: rolling estimation begins February 2013 by construction of the 60-month window.

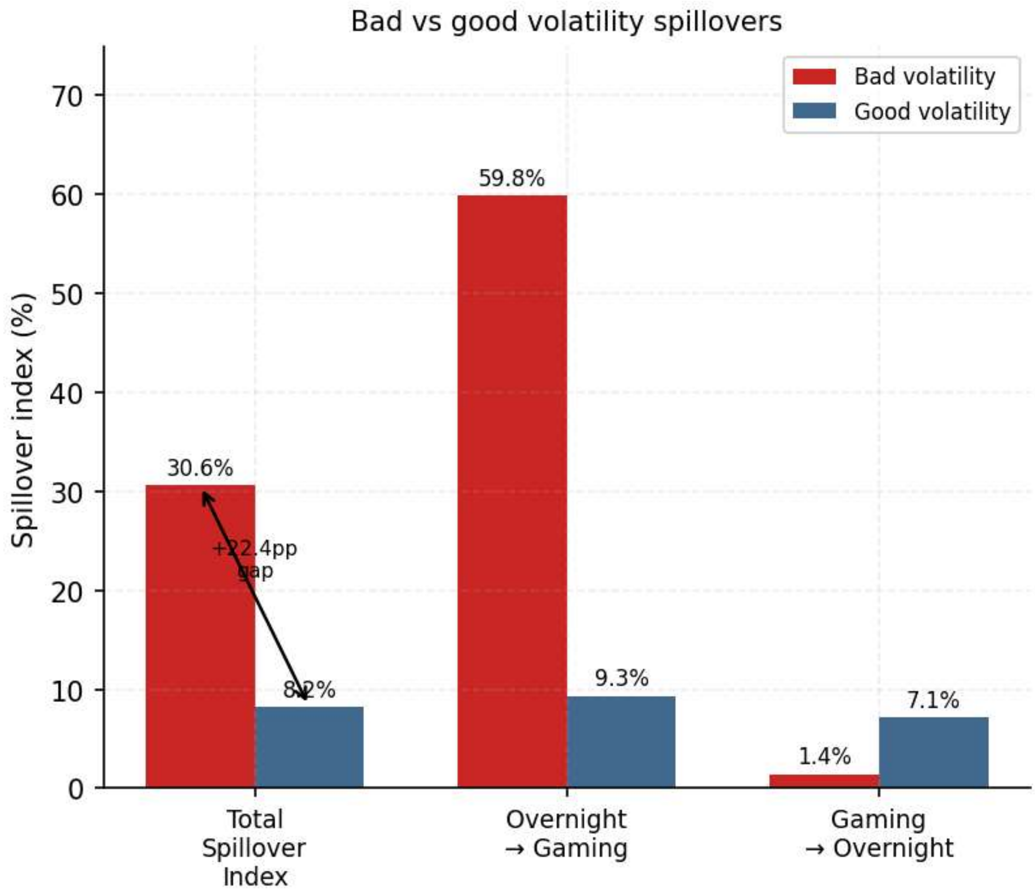
3.5. Asymmetric Spillover: Bad and Good Volatility

The second assumption tested in this paper is that positive and negative shocks transmit across the two series with equal intensity. Table 6 and Figure 5 show this is not the case. The Total Spillover Index for bad volatility is 30.6 percent; for good volatility it is 8.2 percent. The gap of 22.4 percentage points is not a marginal difference around a symmetric baseline; it is a structural feature of how risk propagates in this system. The directional breakdown reinforces this: negative shocks originating in overnight arrivals account for 59.8 percent of gaming revenue's bad volatility forecast error variance, against 9.3 percent for positive shocks. The net directional spillover for bad volatility is +58.4 percentage points, compared with +2.2 percentage points for good volatility. In practical terms, a negative shock to overnight arrivals transmits powerfully to gaming revenue uncertainty, while a positive shock of the same magnitude transmits negligibly. The symmetry assumption fails by a factor of 3.7. This asymmetry compounds the instability result from Section 3.3: not only has the long-run correlation between the two series reversed sign, but within each period, the adverse shocks that would most concern a risk manager travel with far greater force than the favourable shocks that would reassure one.

Table 6. Asymmetric Spillover: Bad versus Good Volatility

Component	Bad volatility (%)	Good volatility (%)	Gap (pp)
Total Spillover Index	30.6	8.2	22.4
Overnight → Gaming (directional)	59.8	9.3	50.5
Gaming → Overnight (directional)	1.4	7.1	-5.7
Net: Overnight (pp)	+58.4	+2.2	56.2

Bad volatility = conditional volatility component attributable to negative innovations. Good volatility = component from positive innovations. VAR(2), H = 10. pp = percentage points.



4. Discussion

The two central results of this paper, the post-2022 correlation sign reversal and the 3.7-fold asymmetry between bad and good volatility transmission, address the same underlying question from different angles. The correlation reversal concerns the long-run structure of the relationship between overnight arrivals and gaming revenue. The volatility asymmetry concerns the short-run dynamics of how shocks travel within whatever structure exists at any given time. Both results challenge assumptions that are commonly embedded in risk models for this type of economy, and their combination has consequences that neither result alone would produce.

The correlation reversal is the more surprising of the two findings, because a sign change that persists for three years is not consistent with a temporary shock to a stable system. The pre-2020 positive correlation of 0.160 was built on a structural relationship that held for twelve years across the GFC, the 2014 to 2016 VIP contraction, and multiple smaller disruptions. The post-2022 negative mean of -0.071 has also proved durable, surviving the full normalisation of visitor volumes. The data from the DCC model can establish the timing and persistence of this reversal, but the model cannot identify its cause. The most parsimonious explanation consistent with the data is that the relationship between overnight arrivals and gaming revenue changed its character after 2022, such that periods of higher overnight arrivals coincided with lower gaming revenue growth, or vice versa. Identifying the precise mechanism requires disaggregated data that are not available in the monthly aggregate series used here, as discussed in Section 5.

The volatility asymmetry result is directly actionable because it quantifies a specific failure mode in symmetric risk models. The 22.4 percentage point gap between bad and good volatility transmission means that a model treating positive and negative shocks equivalently will produce a risk estimate that is structurally too low on the downside. This is not a bias that averages out over time; it is a systematic undercount of the probability mass in the left tail of the gaming revenue distribution. The within-series asymmetry found in Section 3.2, where both overnight arrivals and gaming revenue individually respond more strongly to negative shocks, is the micro-level foundation for this cross-series result. Kim and Wong (2006) and Balli, Tsui and Balli (2019) document the within-series version of this asymmetry in other tourism contexts; this paper documents that it extends across series in Macao's gaming-tourism system. The combination of the two results, a reversed long-run correlation and a 3.7-fold asymmetry in short-run shock transmission, means that risk models calibrated on pre-2020 data and symmetric mechanics will understate downside exposure through two independent channels simultaneously.

5. Conclusion

This paper tests two assumptions that are implicitly embedded in most quantitative risk analyses of Macao's gaming-tourism economy: that the co-movement between overnight visitor arrivals and gaming revenue is stable over time, and that positive and negative shocks transmit across the two series with equal force. Both assumptions fail. The dynamic correlation between overnight arrivals and gaming revenue, which was positive and stable for twelve pre-pandemic years, has remained persistently negative since 2022 despite the full recovery of visitor volumes. The spillover of bad volatility shocks is 30.6 percent, against 8.2 percent for good volatility shocks, a 22.4 percentage point asymmetry that holds across the full sample. These two results are independent of each other in method and operate at different time horizons, yet they point to the same conclusion: the standard modelling assumptions produce risk estimates that are systematically too low on the downside.

The implications for risk management are specific. Any model calibrated on pre-2020 correlation parameters will misrepresent the current relationship between overnight arrivals and gaming revenue, because the sign of that relationship has changed. Any model that applies symmetric shock mechanics will understate downside risk by a factor of approximately 3.7 in cross-series volatility transmission. Both errors apply simultaneously to models that have not been re-estimated since the pandemic.

Future research should pursue two extensions. The first is identifying the mechanism behind the correlation reversal. The most plausible candidates, changes in visitor composition by trip purpose and length of stay, shifts in per-visit gambling intensity, and the structural changes to casino market segments following the 2022 licensing reform including the elimination of the VIP junket system, all require disaggregated data at the visitor and operator level that are not available in the monthly aggregates used here. A study linking individual-level spending survey data to monthly arrival counts would be the most direct way to test these candidate explanations. The second extension is replication across comparable concentrated gaming-tourism economies, particularly Singapore, to determine whether the post-shock correlation reversal is a feature specific to Macao's institutional context or a more general property of gaming destinations subject to abrupt regulatory change.

6. Acknowledgements and Declarations

- Conflicts of Interest. The author declares no conflicts of interest.
- Funding Statement. This research received no internal or external funding.
- Data Availability Statement. The data and replication code that support the findings of this study are openly available at the Zenodo repository: https://doi.org/10.5281/zenodo.20523832. The repository contains all raw data series, Python analysis scripts, and output tables necessary to fully reproduce the results. The original source data (monthly overnight visitor arrivals, same-day visitor arrivals, and gaming tax revenue) were obtained from the Statistics and Census Service (DSEC), Government of the Macao Special Administrative Region, People's Republic of China (https://www.dsec.gov.mo).
- Ethical Approval. As this study relies exclusively on secondary data and involves no human or animal subjects, ethical approval is not required.
- Consent for Publication. Not applicable. This article does not contain any individual person's data in any form (including personal details, images, or videos).

- Author Contributions. Yihuan Lin is the primary author of this manuscript. He conducted this research driven by his passion and profound personal attachment to Macao, China. The author takes full responsibility for the originality and scientific rigor of this work.
- Artificial Intelligence (AI) Use Statement. Anthropic Claude was utilized for grammar improvement, language polishing, and assistance in developing the Python analysis code. The author has audited and verified all code and empirical results and takes full responsibility for their accuracy.
- ORCID. Yihuan Lin: https://orcid.org/0000-0002-8391-7732
- Institutional Review Board (IRB) Statement. Not applicable.

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