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SEASONALITY IN SWISS REIV PRICES

Evidence from Listed Real Estate Investment Vehicles, 2010–2025

Quanthome

/ Key Takeaways

- **Monthly returns in Swiss listed real estate investment vehicles (REIVs) are not uniform throughout the year. July and December tend to be the strongest months; May and October, the weakest. The overall seasonal pattern is statistically detectable but modest in magnitude.**
- **No single month stands out strongly enough to survive rigorous multiple-testing correction, so the pattern should be viewed as a tendency rather than a reliable trading signal.**
- **Dividends matter more than the calendar. Around ex-dividend dates, fund prices drop by roughly 2.9% on average---a mechanical effect reflecting the detachment of the dividend from the share price rather than a loss of investor wealth.**
- **The seasonal profile is broadly similar across residential, commercial, and mixed-use portfolios, and across vehicle types (listed funds and RE shares).**
- **These patterns may inform the timing of capital calls, distributions, or portfolio rebalancing, but transaction costs and limited liquidity in the Swiss listed real estate market make them difficult to exploit profitably.**

/ Why Look at Seasonality?

In equity markets, calendar effects are well documented. The “Sell in May” effect, the January effect, and turn-of-the-month patterns have been studied for decades across global markets. Yet for Swiss traded real estate securities—listed real estate funds (tracked by the SXI Real Estate Funds index, SWIIT), listed real estate shares (tracked by the SXI Real Estate Shares index, REAL), and unlisted funds traded on OTC secondary markets, a combined segment exceeding CHF 60 billion—no systematic study has examined whether similar patterns exist. Real estate foundations (KGAST Immo-Index universe), whose units are redeemed at net asset value without secondary market pricing, are excluded from this analysis.

Understanding whether fund and share prices behave differently depending on the month can help portfolio managers and institutional investors make better-informed decisions about when to deploy capital, schedule distributions, or rebalance allocations. Even if a pattern cannot be exploited for active trading, awareness of it can improve risk budgeting and reduce the likelihood of poorly timed transactions.

This study analyses 82 Swiss listed real estate funds and shares over 15 years (January 2010 to February 2026), representing over 9,300 fund-month observations from Quanthome’s proprietary database.[1]

1. Data extracted on 24 February 2026. The sample comprises 47 exchange-listed funds (SWIIT universe), 18 listed real estate firms (REAL universe), and 17 unlisted funds traded on OTC secondary markets. Only vehicles with at least 12 months of price history are included. Vehicles that delisted or liquidated during the sample period are excluded, which introduces a survivorship bias. Real estate foundations (KGAST universe) are excluded as they lack secondary market prices.

/ Monthly Return Patterns

Figure 1 shows the average return by calendar month across all funds and shares in the sample. The profile reveals a clear rhythm: positive months cluster at the start and end of the year, while the spring-to-autumn period is weaker.

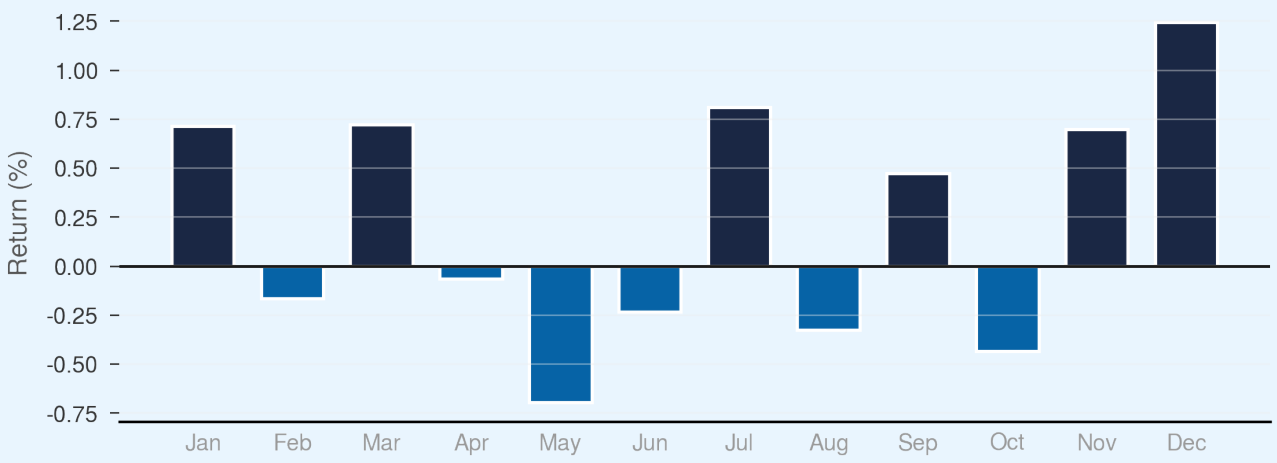

Figure 1. Average monthly returns for Swiss listed real estate funds and shares, 2010–2025.

The best-performing months are July (+1.08%) and December (+1.12%). The weakest are May (−0.60%), October (−0.42%), and August (−0.24%). The popular "Sell in May" adage finds partial support: May is indeed the worst month. However, the supposed summer weakness is interrupted by a strong July, so the pattern is not a continuous dip but rather an alternation of positive and negative months.

A regression model confirms that the twelve months are not all equal—the joint test is significant at the 5% level. However, when each month is tested individually with appropriate correction for multiple comparisons, none survives. In practical terms, this means the seasonal effect is real in aggregate but too diffuse to pin down to any specific month with confidence.

A trend-seasonal decomposition of the market-wide return series yields a seasonal strength score of 0.12 on a 0-to-1 scale, where values below 0.4 indicate weak seasonality. The pattern exists, but it is modest.

	Monthly Return (%)				
Month	**Mean**	**Median**	**Std**	**N**	**p**
Jan	0.638	0.320	3.21	493	–
Feb	0.276	0.289	2.68	912	0.500
Mar	0.076	0.383	4.35	725	0.973
Apr	−0.022	0.114	3.38	689	0.269
May	−0.598	−0.072	3.23	839	0.022
Jun	−0.152	0.170	5.35	871	0.181
Jul	1.077	0.662	3.48	850	0.073
Aug	−0.239	0.000	3.33	835	0.024
Sep	0.517	0.000	16.66†	866	0.905
Oct	−0.416	0.000	4.22	856	0.017
Nov	0.490	0.255	7.74	856	0.475
Dec	1.123	0.960	6.10	516	0.391

Table 1.

Monthly return statistics, 2010–2025.

Notes: Mean, median, std, and N are pooled fund-month statistics. "p" is the raw p-value from an OLS regression of cross-sectional monthly averages on month dummies (January as baseline, Newey-West standard errors). No month survives Holm-Bonferroni correction for multiple comparisons. N varies across months because the panel is unbalanced. Shading indicates the best- and worst-performing months. †September's high standard deviation (16.66%) reflects extreme observations driven by unadjusted corporate actions (capital increases, share splits, rights issues) in specific years. When these outliers are Winsorized, September behaves normally.

/ The Dividend Effect

The most striking calendar-related finding is not about months at all, but about dividends. Swiss listed real estate funds typically distribute dividends once a year, with ex-dates concentrated in April (37% of events) and December (16%).

Around these dates, a clear pattern emerges (Figure 2): prices tend to drift upward in the two weeks before the ex-date—likely reflecting anticipation and last-minute buying—then drop sharply on and after the ex-date as the dividend is detached from the share price. The net effect over an 11-trading-day window around the ex-date is approximately −2.9%, which is highly significant statistically.[2]

It is important to note that this price drop is largely mechanical: since our returns are computed from closing prices alone (without reinvesting dividends), the share price naturally falls by approximately the dividend amount on the ex-date. The ∼2.9% drop is broadly consistent with the historical average dividend yield of Swiss listed real estate vehicles, meaning it is largely wealth-neutral for investors who receive the cash distribution. This mechanical detachment should not be conflated with a genuine anomaly that could be exploited.

This dividend effect likely contributes to the observed monthly seasonality: April and May weakness may partly reflect post-dividend price adjustments, while December and January strength may reflect pre-dividend positioning. By contrast, NAV reporting dates show no meaningful price impact.

2. The cumulative abnormal return over $[-5, +5]$ trading days is −2.89% ($t = -7.00$, $p < 0.001$, based on 152 events with complete data). Over the wider $[-20, +20]$ window, the effect is −2.88% ($t = -4.37$, $p < 0.001$).

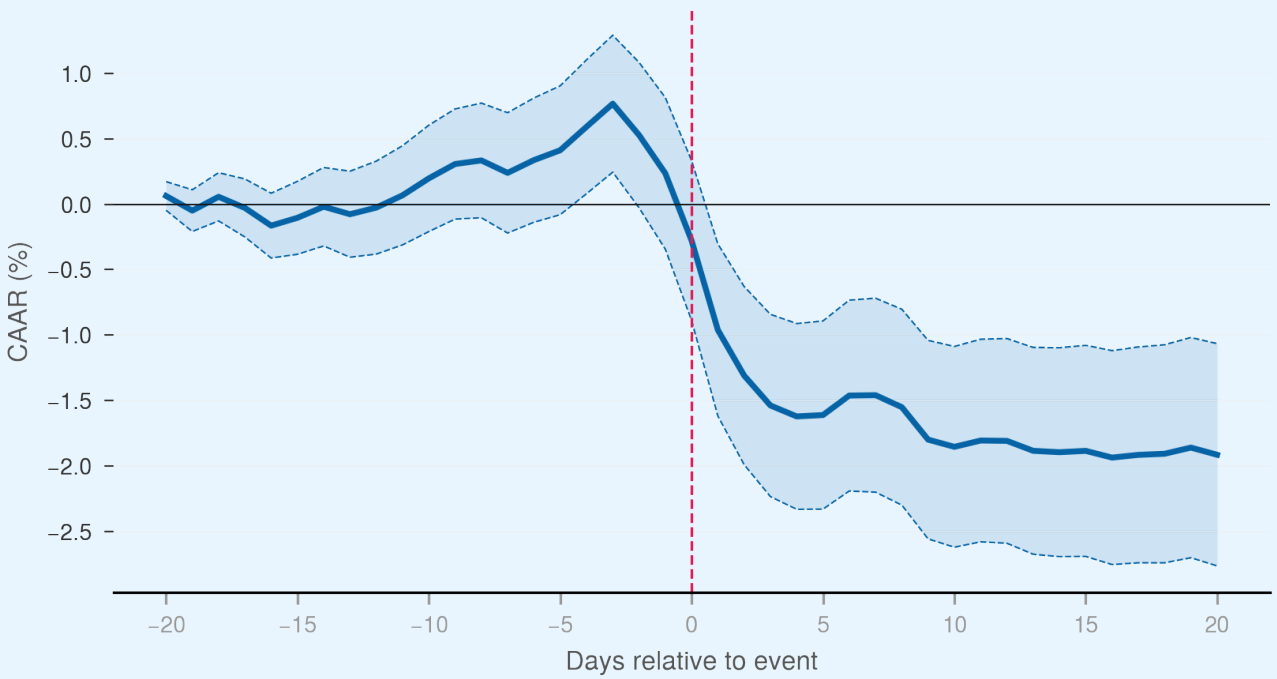

Figure 2. Average abnormal price behaviour around dividend ex-dates. Prices tend to rise in the 10 days before the ex-date, then drop sharply. The shaded area shows a 95% confidence band.

CAAR 95% CI Event day

/ Does Vehicle Type Matter?

We segment vehicles by their actual building composition (majority residential, commercial, or mixed-use) rather than their official classification, using market-value data from the latest financial reports.

The heatmap (Figure 3) shows that the seasonal profile is broadly consistent across segments. Residential, commercial, and mixed-use vehicles all share a similar monthly rhythm. When tested formally, none of the 36 pairwise month-segment comparisons shows a significant difference after correction for multiple testing.

By regulatory legal form, the picture is similar (Figure 4). Investment vehicles and real estate firms display comparable seasonal shapes, with minor amplitude differences. The seasonal pattern appears to be a market-wide phenomenon rather than a segment-specific one.

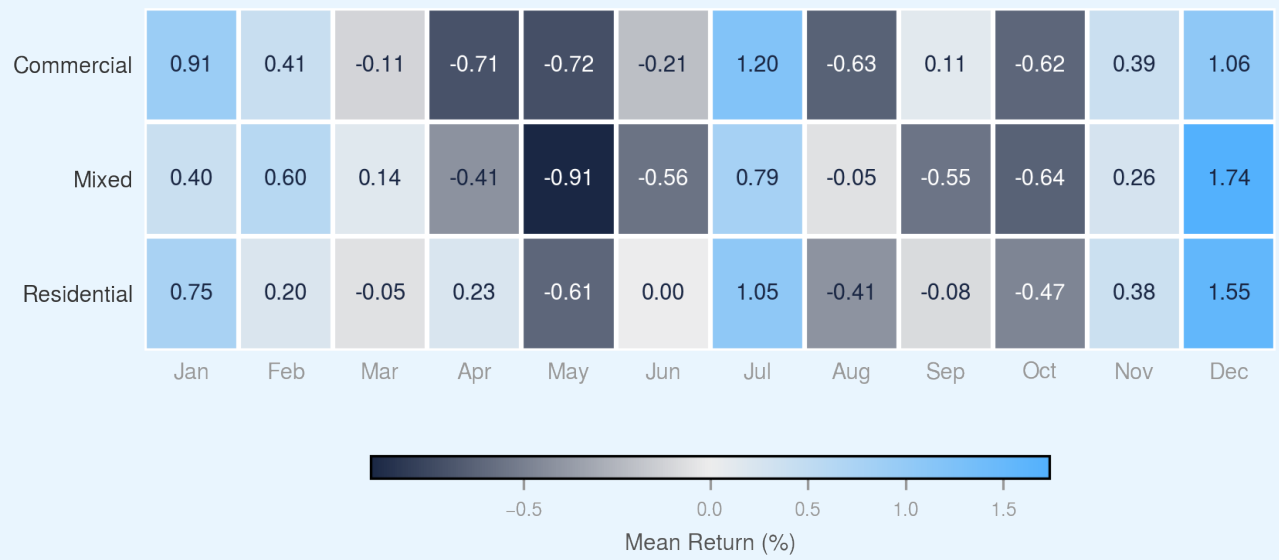

Figure 3. Average monthly returns by building composition. The seasonal rhythm is similar across all three segments.

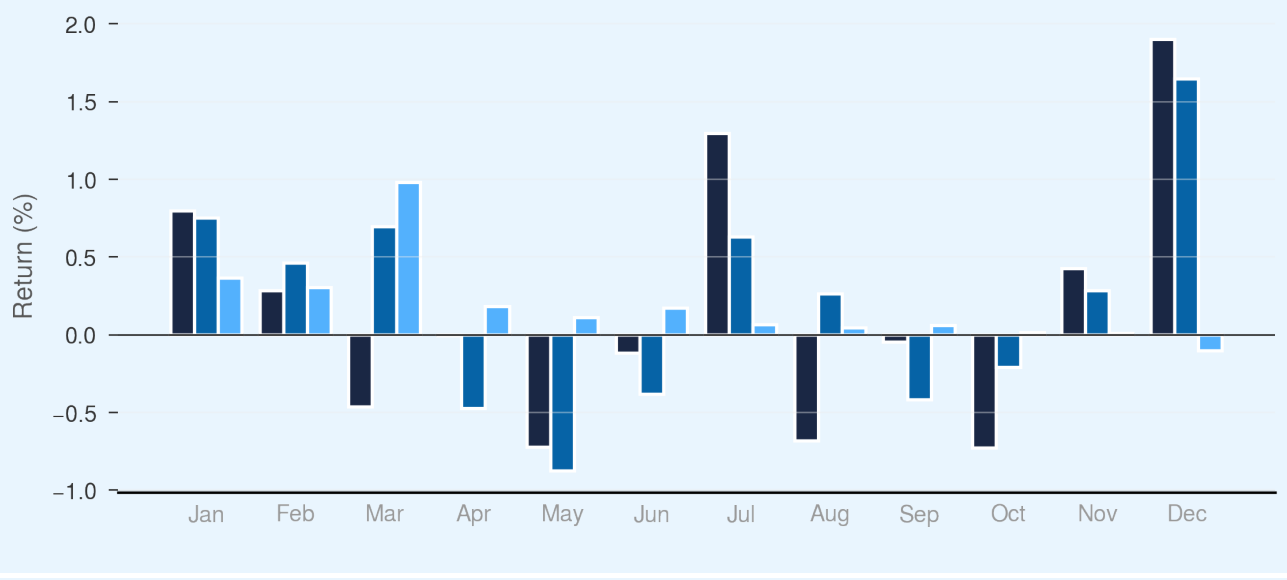

Figure 4. Monthly returns by regulatory vehicle type. The seasonal shape is shared across categories.

/ How Robust Are These Patterns?

Across market regimes. We split the sample into four periods—post-GFC recovery (2010–2014), yield compression (2015–2019), COVID and aftermath (2020–2021), and the SNB rate normalisation era (2022+). The broad seasonal shape persists across regimes (Figure 5). The non-parametric Kruskal-Wallis test does not reach significance in any sub-period (as expected given the smaller sample sizes), though the OLS joint month test remains significant in each sub-period—suggesting that the

seasonal pattern is persistent but requires the parametric model's greater power to detect.

After removing outliers. Capping extreme returns at the 1st and 99th percentiles strengthens the statistical fit, confirming that a few large outliers—particularly in September—add noise that partially obscures the seasonal signal. The core pattern remains unchanged.

Premium-to-NAV (agio). Monthly changes in the average agio do not show significant seasonality. This suggests that both prices and NAVs tend to move in tandem on a seasonal basis, or that the effect is too small to detect with the available data.

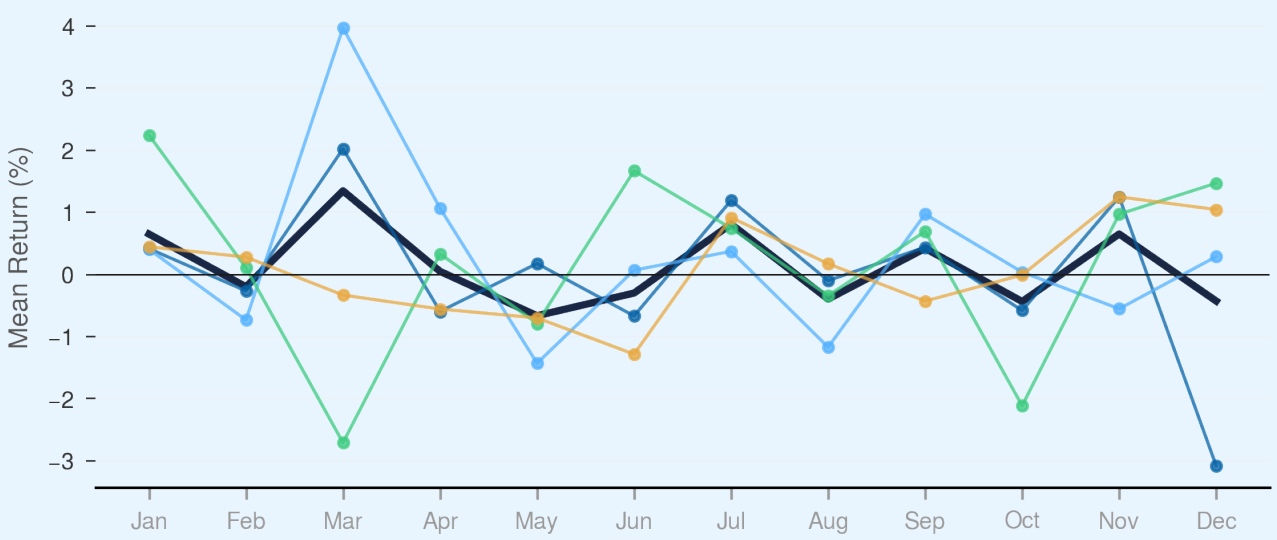

Figure 5. Monthly return profiles across market regimes. The broad shape shows some persistence despite very different market environments.

/ Caveats for Investors

Not a trading signal. The seasonal differences are modest—on the order of 1–2 percentage points between the best and worst months—and no single month is reliably strong or weak enough to anchor a strategy.

Transaction costs are real. Many Swiss listed real estate vehicles trade thinly, with wide bid-ask spreads. After accounting for realistic trading frictions, the observed seasonal differences would likely vanish.

Survivorship bias. Our sample includes only vehicles that were active at the time of extraction. Vehicles that delisted or liquidated during 2010–2025 are excluded, which may overstate average returns.

Past patterns may not persist. The seasonal shape shows some stability across market regimes, but 15 years of data provides limited statistical power. The pattern could weaken or shift as market structure evolves.

Price returns only. Returns are computed from closing prices and do not include reinvested dividends (total return). In months with heavy ex-dividend activity (April, May), this introduces a negative bias that may partly explain the observed seasonal weakness.

Autocorrelation in illiquid markets. Some of the monthly pattern may reflect stale pricing rather than genuine return seasonality. Thinly traded vehicles may show delayed price reactions that create artificial month-to-month patterns.

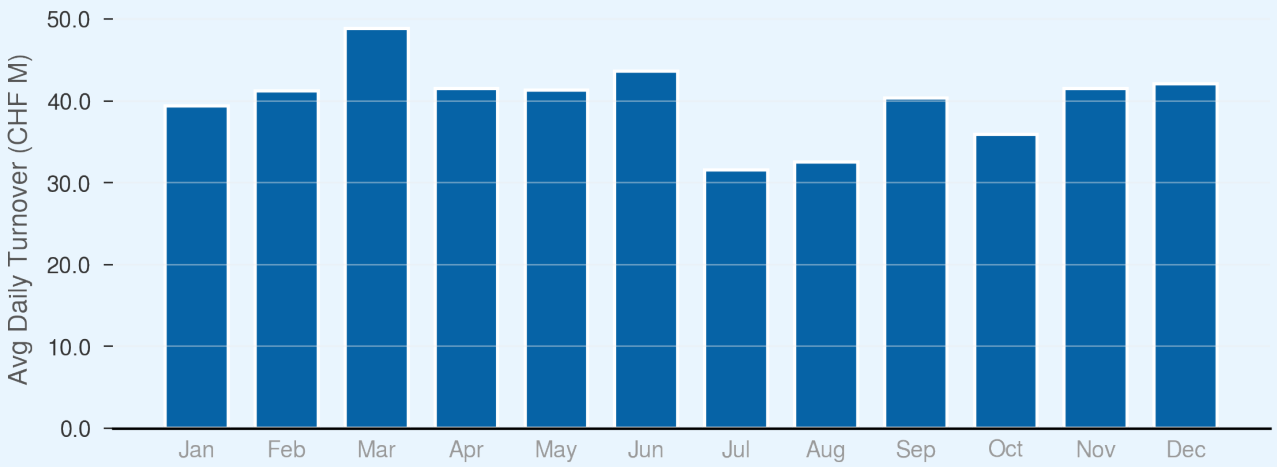

Figure 6. Average daily trading turnover (CHF millions) by calendar month, 2010–2025. The limited and uneven liquidity reinforces the difficulty of exploiting seasonal patterns.

Methodology Notes

For readers interested in the technical details, we summarise the statistical approach below.

Returns are computed as log returns from month-end closing prices. These are price returns only; dividends are not reinvested. **The joint seasonality test** uses an OLS regression of cross-sectional average monthly returns on eleven month dummies (January as baseline), with Newey-West standard errors to account for serial correlation. Individual month p-values are adjusted using the Holm-Bonferroni correction. **The non-parametric test** uses the Kruskal-Wallis H-statistic on cross-sectional averages (approximately 16 observations per month), not on the raw panel, to avoid inflating the test from cross-fund dependence.

The event study estimates a market model over a 100-day pre-event window, then measures cumulative abnormal returns in a $\pm$20-day event window. The market return is the equal-weighted daily return across all funds and shares in the sample (which introduces a minor bias as the event fund is included). Significance is assessed by computing total window CARs per event and performing a cross-sectional t-test. Because Swiss real estate fund dividends cluster heavily in time (37% of ex-dates fall in April), the cross-sectional independence assumption is imperfect and the reported t-statistics may be somewhat overstated.

STL decomposition uses period = 12, seasonal = 13, trend = 19, with robust estimation. The seasonal strength metric F_S follows Wang et al. (2006), with the interpretive thresholds (above 0.64 strong, below 0.4 weak) drawn from Hyndman & Athanasopoulos (2021).

Vehicle segmentation classifies vehicles by majority building composition ($>$50% residential, commercial, or mixed by market value) from the latest financial reports. The "mixed" category is a heterogeneous catch-all. Legal form segmentation uses the regulatory classification. Cross-sectional segment comparisons use returns Winsorized at the 1st and 99th percentiles to prevent corporate-action artefacts (e.g. reverse stock splits) from distorting small-segment averages.

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