Temporal Aggregation and Seasonality in Autocorrelations of Stock Returns

Abstract

A decomposition shows that the AR(1) coefficient of time-aggregated stock returns varies with the aggregation interval whenever daily autocorrelations exhibit seasonality. Consistent with this mechanism, we document time-varying seasonality in the AR(1) coefficient estimates for weekly and monthly stock-market returns. We also uncover consistent time-varying seasonality in daily autocorrelations, which is likely driven by market structure and trading technology. We further find time-varying asymmetries and interactions between the weekly and monthly seasonalities, pointing to a multilayered, dynamic return-generation process.

JEL Classification: G12

keywords: Temporal Aggregation, Autocorrelation, Stock Return, Seasonality

1 Introduction

Aggregating higher-frequency returns to lower frequencies is standard in empirical finance. Researchers often combine daily returns to construct long-horizon (e.g., monthly) returns that better suit estimation and testing or match the availability of macroeconomic and accounting data. An oft-cited benefit is noise reduction.[1] However, temporal aggregation can oversmooth the data, discarding informative variation. A further—often overlooked—issue is that aggregation can induce features that are artifacts of the procedure itself. Consequently, statistical analyses may yield different results under different aggregation schemes, raising concerns about the validity of statistical inferences based on time-aggregated returns.[2]

This paper studies how the statistical properties of time-aggregated returns depend on the start and end days of the aggregation interval. In our baseline analysis, we examine how the first-order autocorrelation, AR(1), of weekly stock-market index returns varies with the choice of weekly interval. Although calendar weeks are standard, there is no requirement to use them; non-calendar weeks are equally valid and have beem used in prior work (e.g., Lo and MacKinlay, 1988; Boudoukh et al., 1994; Campbell et al., 1997). We document that the AR(1) coefficient of weekly returns is highly sensitive to the interval definition. For example, for the CRSP value-weighted index over 1953–2024, weekly returns constructed with Tue-Mon$^+$, the interval from Tuesday to next Monday, yield a significantly negative AR(1) estimate of -0.043 ($t = -2.658$), whereas the calendar-week construction produces an estimate close to zero (-0.001, $t = -0.055$). Hence, a researcher testing the random walk hypothesis with the AR(1) estimate of weekly returns would reject the null using Tue-Mon$^+$ returns but fail to reject it using calendar-week returns. Subperiod results not only confirm

[1]For example, Scholes and Williams (1977), Dimson (1979), and Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983b) recommend using long return intervals to mitigate market-microstructure frictions in beta estimation.

[2]Temporal aggregation has been examined extensively in the econometric literature; see Silvestrini and Veredas (2008) for a survey. Prior studies primarily analyze how aggregation affects parameters and inference in structural (parametric) time-series models—assumptions we do not impose here.

large variation in AR(1) coefficient estimates across different intervals but also reveal sharp shifts over time. In 1953–1988, the AR(1) coefficient is significantly positive for every interval except Tue-Mon$^+$; in 1989–2024, it is significantly negative for every interval.

What makes the weekly AR(1) depend on the aggregation interval? We show that the AR(1) autocorrelation of n-day-aggregated returns can be written as a linear combination of the daily autocorrelations at lags 1 through $(2n-1)$. If the daily autocorrelation structure is time-homogenous—as under a stationary ARMA process—the choice of start/end days is immaterial. By contrast, if the daily autocorrelations exhibit seasonality, the AR(1) of the aggregated series depends on the interval definition. For illustration, suppose only Monday-Tuesday returns are negatively correlated while all other pairs of weekdays, including those days apart, are uncorrelated. Calendar-week aggregation places Monday and Tuesday within the same week, so this negative pair does not load into the correlation between adjacent weeks, yielding an AR(1) near zero. Defining weeks as Tue-Mon$^+$ instead splits that pair across consecutive weeks, so the Monday-Tuesday negative correlation translates into a negative AR(1) for Tue-Mon$^+$ weekly returns.[3]

We document pronounced seasonality in daily autocorrelations that aligns with the cross-interval variation in weekly AR(1) estimates. Over 1953–2024, more than half of the relevant coefficients are statistically significant at the 10% level or better. For example, Mon$^+$ is positively correlated with all five days of the previous week, three at the 1% level;[4] by contrast, Tue$^+$ is negatively correlated with all five days of the previous week, two at the 1% level. Appropriately averaging the daily autocorrelations closely reproduces the AR(1) coefficients of weekly returns. Subsample analyses further show that the seasonality in daily autocorrelations is time-varying, mirroring the time variation in weekly AR(1) estimates. For instance, during 1953–1988, Mon$^+$ correlations with each of the five days of the previous week are

[3]The Lo and MacKinlay (1988) variance-ratio test also produces different results across the two intervals.

[4]Prior studies have examined some—though not all—of these seasonal patterns in samples ending in the 1990s (Keim and Stambaugh, 1984; Bessembinder and Hertzel, 1993; Boudoukh et al., 1994).

significantly positive at the 1% level; during 1989–2024, only Thursday and Friday remain positive, with smaller magnitudes and lower significance. Taken together, the evidence suggests that understanding the seasonality of weekly AR(1) estimates requires understanding the seasonality of daily autocorrelations.

The literature offers several explanations for weekday seasonality in mean returns and for the AR(1) in daily returns, but none applies directly to the day-of-week seasonality in daily autocorrelations that we document. We posit mechanisms tied to investors' trading behavior in the presence of market frictions.[5] For example, during 1953–1988, Mon+ is positively correlated with each of the five prior weekdays, consistent with gradual underreaction within the preceding week; by contrast, during 1989–2024, the Monday–Tuesday pair is negatively correlated, consistent with a Tuesday reversal of Monday overreaction. That said, such behavioral stories struggle to account for higher-order terms—for instance, the significantly positive correlation between Tue and Mon^{++} (0.112, $t = 4.196$), where $^{++}$ denotes the week after next week—suggesting that a full explanation must go beyond simple under-/overreaction narratives.

While we do not claim a universal framework for the seasonality in daily autocorrelations, we conduct additional analyses that shed light on potential drivers. First, following Bessembinder and Hertzel (1993), we examine the subsample of Tuesdays that follow nontrading Mondays. These Tuesdays exhibit autocorrelation patterns that differ from other Tuesdays and instead resemble those of Mondays, extending Bessembinder and Hertzel's finding to higher-order autocorrelations. This evidence is consistent with trading activity—and its absence—shaping the day-of-week seasonality we document.

Time variation in the seasonality of daily autocorrelations encompasses the recent evi-

[5] Abraham and Ikenberry (1994) and Chen and Singal (2003), for example, argue that investors' trading on Fridays and Mondays contributes to weekend return patterns. Hu, Jin, and Wang (2025) summarize explanations for nonzero AR(1) coefficients into four categories: nonsynchronized trading, sluggish response to information, time-varying expected returns, and liquidity effects. They conclude that multiple mechanisms are required to match the empirical evidence.

dence that the AR(1) of daily stock returns has shifted from positive to negative (Baltussen et al., 2019; Lewellen, 2022; Bogousslavsky et al., 2025; Hu et al., 2025). For each of lags 1–9, we measure the strength of day-of-week seasonality by the "range"—the difference between the maximum and minimum coefficients across weekdays—computed in a ten-year rolling window. The nine ranges vary markedly over time and display a distinctive correlation structure: low-order ranges are mostly positively correlated with one another, as are high-order ranges, whereas cross-group correlations tend to be negative. These patterns indicate shifting seasonality in daily autocorrelations. Inspecting the time paths of the ranges confirms the view of Hu, Jin, and Wang (2025) that the evolution of weekly AR(1) seasonality is tied to changes in market structure and trading technology.[6]

Motivated by the daily AR(1) asymmetry documented by Hu, Jin, and Wang (2025), we test for sign asymmetry in day-of-week autocorrelations up to lag 9. We find pronounced asymmetry: for many weekday–lag pairs, the autocorrelation differs when conditioning on negative versus positive returns. Hu, Jin, and Wang (2025) report that the daily AR(1) is largely accounted for by the negative-state coefficient. Our more granular results show that some seasonal patterns are primarily driven by negative-state autocorrelations, whereas others are driven by positive-state autocorrelations. The asymmetry is also time-varying: many sign-conditional autocorrelations change sign over time.

Our general AR(1) decomposition extends naturally to monthly horizons, where we also find seasonal patterns in AR(1) estimates. Over 1926–2024, the AR(1) coefficient is significantly positive when the interval begins and ends near the turn-of-the-month (e.g., calendar months), but insignificant when the interval begins and ends around the 10th. For example, the calendar month (M1) yields an estimate of 0.088 ($t = 3.042$), whereas the 10th–9th interval (M10) yields 0.013 ($t = 0.457$). This seasonality is time-varying: estimates are more significant early in the sample and mostly insignificant in recent decades. Notably, even in

[6] Baltussen, van Bekkum, and Da (2019), for example, link the shift of AR(1) to the increasing popularity of index products.

the latter half, the cross-interval profile is U-shaped—lowest around the 10th and highest near month-ends—with a peak-to-trough difference that remains statistically significant and comparable to that in the first-half subsample.

Given the seasonal patterns in AR(1) estimates across weekly and monthly interval definitions, we explore cross-frequency interactions. We partition each month into four within-month quarters of roughly equal length and assign each weekly observation to a quarter by the week's end date. Some interesting cross-frequency interactions emerge. For example, over 1953–1988, the second within-month quarter is a key driver of the positive AR(1) in weekly returns, whereas during 1989–2024 it does not contribute to the negative AR(1). These interactions underscore a multilayered, cross-frequency seasonal structure in daily autocorrelations. To assess generality beyond the U.S. market, we extend the baseline weekly analysis to eight international equity markets and document analogous cross-interval variation in weekly AR(1) estimates, as well as consistent seasonality in daily autocorrelations.

This paper contributes to the literature on seasonality in daily stock returns. Prior studies primarily examine seasonal patterns in average returns—for example, the day-of-the-week effect (French, 1980; Gibbons and Hess, 1981) and the turn-of-the-month effect (Ariel, 1987).[7] Our focus instead is on seasonality in the serial dependence structure: specifically, the AR(1) coefficient of time-aggregated returns and the corresponding seasonality in daily autocorrelations.

The literature on return autocorrelations has expanded substantially over the past four decades.[8] While most work emphasizes the nonseasonal first-order autocorrelation, we ex-

[7]A partial list of subsequent studies on the day-of-the-week and turn-of-the-month effects include Keim and Stambaugh (1984), Jaffe and Westerfield (1985), Lakonishok and Smidt (1988), Connolly (1989), Ogden (1990), Chang, Pinegar, and Ravichandran (1993), Abraham and Ikenberry (1994), and Chen and Singal (2003).

[8]A partial list of papers include Keim and Stambaugh (1984), Atchison, Butler, and Simonds (1987), Lo and MacKinlay (1988); Lo and Craig MacKinlay (1990), Bessembinder and Hertzel (1993), Campbell, Grossman, and Wang (1993), Mech (1993), Boudoukh, Richardson, and Whitelaw (1994), Chordia and Swaminathan (2000), Ahn, Boudoukh, Richardson, and Whitelaw (2002), Hou (2007), Baltussen, van Bekkum, and Da (2019), Lewellen (2022), Bogousslavsky, LeBaron, and Pontiff (2025), and Hu, Jin, and Wang (2025).

tend the line of research examining seasonality in autocorrelations. Keim and Stambaugh (1984) and Bessembinder and Hertzel (1993) are among the first to document weekly seasonality in the first-order autocorrelation around nontrading days. Boudoukh, Richardson, and Whitelaw (1994) report notable day-of-week differences in daily autocorrelations up to lag 5 and connect these differences to variation in weekly AR(1) across alternative interval definitions. Generalizing their insight, we motivate the study of seasonality in daily autocorrelations from a temporal-aggregation perspective for arbitrary interval lengths and show analytically how day-of-interval seasonality feeds into the first-order autocorrelation of low-frequency returns. Empirically, at the weekly horizon we extend the analysis to lag 9—necessary to fully account for the weekly AR(1) under aggregation—and update the sample through 2024, documenting pronounced time variation in seasonality alongside the shift toward reversal in recent decades (Baltussen et al., 2019; Lewellen, 2022; Bogousslavsky et al., 2025; Hu et al., 2025). We further extend Hu, Jin, and Wang (2025) by documenting sign asymmetry in day-of-week autocorrelations up to lag 9. Beyond weekly seasonality, we also find monthly seasonality; combining weekly and monthly evidence yields a more complete picture of the evolution of serial dependence in stock-market returns. Finally, we show that similar patterns—seasonality in weekly AR(1) and in daily autocorrelations—appear in international markets, extending the findings of Baltussen, van Bekkum, and Da (2019) on first-order daily autocorrelation in a setting without explicit seasonality.

Existing studies on the temporal aggregation of stock returns have largely not considered return autocorrelations. Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983a) demonstrate a bias in estimated beta—"the intervalling effect"—arising from delayed price adjustment due to market frictions. Bondarenko (2014) and Neuberger (2012) examine links between high- and low-frequency estimates of variance and skewness, and Kole, Markwat, Opschoor, and van Dijk (2017) analyze the impact of time aggregation on Value-at-Risk (VaR) forecasts. The prior work typically posits a high-frequency data-generating process and studies the implications for low-frequency statistics. By contrast, we impose no assumptions about the daily data-generating process and emphasize that low-frequency inference depends on the choice of aggregation interval. Our objective is to provide a more complete picture of return dynamics to help identify the underlying market mechanisms.

The rest of the paper is organized as follows. Section 2 presents evidence that the weekly AR(1) coefficient depends on the definition of the weekly interval. Section 3 explains these findings by decomposing the AR(1) coefficient and documenting consistent day-of-week seasonality in daily autocorrelations. Section 4 provides additional analyses and robustness checks. Section 5 concludes.

2 AR(1) of Weekly Returns

We use daily log returns on the CRSP value-weighted (VW) market index to illustrate how interval choice affects statistical properties—specifically, the AR(1) coefficient ρ—of the corresponding weekly returns. We estimate ρ via the OLS regression:

$$r_{t+1} = \mu + \rho r_t + \varepsilon_{t+1}, \tag{1}$$

where r_t is the log return of weekly interval t, which is the sum of the log returns of the trading days in week t under that definition. We focus on the 1953–2024 sample and two subperiods: 1953–1988 and 1989–2024. We consider five weekly interval definitions based on start and end days—Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$—where "+" denotes the following calendar week. Mon-Fri corresponds to the conventional calendar week construction of weekly returns, whereas the alternative definitions that straddle the weekend have also been used in prior studies.

The daily CRSP data begin in 1926. Until June 1952, however, Saturday was a trading day (albeit with shorter hours than other weekdays). Accordingly, the calendar week then ran Monday–Saturday, and a sixth weekly interval—Sat-Fri$^+$—was also feasible. For consistency, most of our analyses use the post-1952 period. To address concerns about the pre-1953 sample, we also report baseline estimates of ρ for the five weekly intervals that exclude Sat-Fri$^+$ over 1926–2024 and for two subperiods, 1926–1974 and 1975–2024.[9]

Table 1 reports the estimates of ρ for the five weekly interval definitions across different periods. In Panel A (1953–2024), ρ ranges from -0.043 for Tue-Mon$^+$ to 0.021 for Thu-Wed$^+$. The Tue-Mon$^+$ estimate is significant at the 1% level ($t = -2.658$), whereas the other four intervals are insignificant; in particular, the calendar week (Mon-Fri) is essentially zero (-0.001, $t = -0.055$). Thus, a test of $H_0 : \rho = 0$ over the full sample would reject under Tue-Mon$^+$ but would fail to reject under the other interval definitions.

Panels B and C show pronounced but opposite patterns across subperiods: for all five interval definitions, ρ is positive in 1953–1988 and negative in 1989–2024. During 1953–1988, ρ is insignificant only for Tue-Mon$^+$; in 1989–2024, it is significant at least at the 10% level for all intervals. These offsetting signs reconcile the weaker full-sample results in Panel A. For example, the significantly negative Tue-Mon$^+$ estimate over 1953–2024 reflects an insignificant 0.011 in 1953–1988 combined with a significant -0.085 in 1989–2024.

Panel D reports results for the extended 1926–2024 sample, which includes years when Saturday was a trading day. Across interval definitions, ρ ranges from -0.015 (Tue-Mon$^+$) to 0.044 (Thu-Wed$^+$). The Thu-Wed$^+$ estimate is significant at the 1% level ($t = 3.173$) and Fri-Thu$^+$ at the 10% level for ($t = 1.913$); the other three intervals are insignificant. For the calendar week defined as Mon-Sat, ρ is basically zero (0.016, $t = 1.151$). Relative to Panel A (1953–2024), extending the sample shifts the cross-interval profile from mostly negative to mostly positive, consistent with more positive weekly autocorrelation in the pre-1953 years. A test of $H_0 : \rho = 0$ over 1926–2024 would be rejected at the 1% level for Thu-Wed$^+$ but, as in Panel A, not for Wed-Tue$^+$.

Panels E and F exhibit the same contrast as Panels B and C across subperiods: for all

[9]The results for Sat-Fri$^+$ over 1926–1952 are available upon request.

five interval definitions, ρ is positive in 1926–1974 and negative in 1975–2024. During 1926–1974, ρ is large and highly significant for Thu-Wed^{+} (0.083, t=4.237) and Fri-Thu^{+} (0.085, t=4.337), insignificant for Tue-Mon^{+} (0.015, t=0.754) and at the 10% level for Wed-Tue^{+} (0.035, t=1.748). For the calendar week (Mon-Sat), ρ is significant at the 5% level (0.044, $t = 2.248$). In 1975–2024, the calendar-week estimate is insignificant (-0.022, $t = -1.154$), whereas Tue-Mon^{+}, Wed-Tue^{+}, and Fri-Thu^{+} are significant at least at the 10% level. These offsetting subperiod results reconcile the more moderate full-sample values in Panel D.

Two remarks are in order. First, the estimate of ρ for every weekly interval varies over time, switching from positive in the first subperiod to negative in the second—a phenomenon we explore in detail. Second—and central to our thesis—the magnitude and statistical significance of ρ for a given sample period differ across interval definitions. This dependence of inference on the choice of interval is puzzling and warrants further investigation.

Table 1 also shows that mean returns do not vary materially across interval definitions. Likewise, the non-calendar-week intervals have standard deviations similar to the calendar week, even though they straddle the weekend (**?**). By contrast, skewness and kurtosis vary markedly with the interval. For example, in Panel A (1953–2024), Wed-Tue^{+} and Fri-Thu^{+} display the most negative skewness (-1.118 and -1.141) and the highest kurtosis (14.211 and 14.393). Panels B and C indicate that Wed-Tue^{+} has the lowest skewness and highest kurtosis in the first half of the sample, whereas Fri-Thu^{+} does so in the second half. These results suggest that higher-order properties of weekly returns—beyond the AR(1) coefficient—are highly sensitive to the interval choice and the sample period. Accordingly, empirical analyses using weekly returns warrant caution.

3 Seasonality in Daily Autocorrelations

What drives the dependence of ρ for weekly returns on the interval definition? We address this by decomposing ρ into daily components, showing how day-of-week seasonality in daily autocorrelations maps into variation in weekly ρ across interval definitions.

3.1 Decomposition of AR(1) Coefficient of n-Day Returns

Suppose log daily returns are partitioned into nonoverlapping, consecutive n-day intervals (e.g., weeks). Let $r_{t,1}, ..., r_{t,n}$ denote the daily returns within interval t. The full sample comprises certain number of intervals:

$$(r_{1,1}, ..., r_{1,n}), (r_{2,1}, ..., r_{2,n}), ..., (r_{t,1}, ..., r_{t,n}), (r_{t+1,1}, ..., r_{t+1,n}), ...$$

For each interval t, the aggregated return is $\sum_{i=1}^{n} r_{t,i}$. Assuming, without loss of generality, zero mean daily returns, the AR(1) coefficient of n-day aggregated returns is expressed as:

$$\begin{aligned} \rho &= \frac{\mathrm{Cov}(\sum_{i=1}^{n} r_{t,i}, \sum_{j=1}^{n} r_{t+1,j})}{\mathrm{Var}(\sum_{i=1}^{n} r_{t,i})} \\ &= \frac{\sum_{i,j=1}^{n} \mathrm{Cov}(r_{t,i}, r_{t+1,j})}{\mathrm{Var}(\sum_{i=1}^{n} r_{t,i})}. \end{aligned} \tag{2}$$

The numerator in (2) is the sum of the covariances of pairs of daily returns, one of which from interval t and the other from interval $t+1$. There are n^2 $(1 \leq i, j \leq n)$ covariance terms, each of which represents an order-$(n-i+j)$ daily autocovariance, where $(n-i+j)$ ranges from 1 for $\mathrm{Cov}(r_{t,n}, r_{t+1,1})$ to $2n-1$ for $\mathrm{Cov}(r_{t,1}, r_{t+1,n})$. It is critical to note that changing the interval's start and end days alters which daily autocovariances enter—and with what multiplicities—so that the value of ρ changes whenever these autocovariances vary (e.g., with day-of-week seasonality). Note that ρ can also vary through the denominator, since the aggregated variance depends on the interval definition. In practice, however, Table 1 shows that the weekly variance does not differ significantly across interval definitions.

For illustrative purposes, consider $n = 2$. Daily returns can be partitioned into nonoverlapping two-day intervals in two distinct ways—starting on day 1 or on day 2—yielding two alternative constructions. Assume the first one to be:

$$..., (r_{t-1,1}, r_{t-1,2}), (r_{t,1}, r_{t,2}), (r_{t+1,1}, r_{t+1,2}), ...$$

The numerator of ρ is then expressed as:

$$\mathrm{Cov}(r_{t,1}+r_{t,2}, r_{t+1,1}+r_{t+1,2}) = \mathrm{Cov}(r_{t,1}, r_{t+1,1})+\mathrm{Cov}(r_{t,1}, r_{t+1,2})+\mathrm{Cov}(r_{t,2}, r_{t+1,1})+\mathrm{Cov}(r_{t,2}, r_{t+1,2}). \tag{3}$$

The second construction is:

$$..., (r_{t-1,2}, r_{t1,1}), (r_{t,2}, r_{t+1,1}), (r_{t+1,2}, r_{t+2,1}), ...$$

The numerator of ρ for the second two-day return series is:[10]

$$\mathrm{Cov}(r_{t,2}+r_{t+1,1}, r_{t+1,2}+r_{t+2,1}) = \mathrm{Cov}(r_{t,2}, r_{t+1,2})+\mathrm{Cov}(r_{t,2}, r_{t+2,1})+\mathrm{Cov}(r_{t,1}, r_{t,2})+\mathrm{Cov}(r_{t,1}, r_{t+1,1}). \tag{4}$$

If daily returns are uncorrelated, changing the interval does not affect ρ because both numerators in (3) and (4) are zero. When daily returns are autocorrelated, however, the two numerators can differ. Comparing the right-hand sides of (3) and (4), they coincide if the following conditions hold:

$$\mathrm{Cov}(r_{t,1}, r_{t,2}) = \mathrm{Cov}(r_{t,2}, r_{t+1,1}), \tag{5}$$

$$\mathrm{Cov}(r_{t,1}, r_{t+1,2}) = \mathrm{Cov}(r_{t,2}, r_{t+2,1}). \tag{6}$$

Condition (5) states that the within-interval lag-1 autocovariance is invariant to the interval definition: the two sides correspond to the covariances of the daily returns within each of the two interval types, respectively. Condition (6) states that the lag-3 autocovariance does not

[10] We assume $\mathrm{Cov}(r_{t+1,1}, r_{t+1,2}) = \mathrm{Cov}(r_{t,1}, r_{t,2})$ and $\mathrm{Cov}(r_{t+1,1}, r_{t+2,1}) = \mathrm{Cov}(r_{t,1}, r_{t+1,1})$. This is reasonable because, for each equation, the two daily pairs on the two sides are differed by a two-day shift.

depend on the choice of the starting day. Both conditions are satisfied if daily autocovariances are time-homogeneous—that is, invariant to the starting day. Otherwise, (5) and (6) need not hold. In particular, if lag-1 or lag-3 daily autocovariances exhibit seasonality, the two-day aggregates constructed under the two partitions will produce different values of ρ.

The two-day analysis extends straightforwardly to intervals of arbitrary length, though the general expressions are cumbersome to present. The key takeaway is that day-of-week seasonality in daily autocorrelations induces variation in the AR(1) of n-day returns across interval definitions.

3.2 Weekly Interval

We illustrate the decomposition of ρ and the impact of interval choice using weekly returns for 1953–2024, with subperiods 1953–1988 and 1989–2024. Consider a partition of daily returns into nonoverlapping weekly intervals: ..., $(r_{t,1}, ..., r_{t,5})$, ..., and let $\sum_{i=1}^{5} r_{t,i}$ denote the aggregated weekly return of interval t. The first-order autocovariance of weekly returns is expressed in three ways:

$$\begin{aligned}
\mathrm{Cov}(\sum_{i=1}^{5} r_{t,i}, \sum_{j=1}^{5} r_{t+1,j}) &= \sum_{i=1}^{5} \mathrm{Cov}(r_{t,i}, \sum_{j=1}^{5} r_{t+1,j}) && (7)\\
&= \sum_{j=1}^{5} \mathrm{Cov}(\sum_{i=1}^{5} r_{t,i}, r_{t+1,j}) && (8)\\
&= \sum_{i,j=1}^{5} \mathrm{Cov}(r_{t,i}, r_{t+1,j}). && (9)
\end{aligned}$$

Under the calendar-week convention, let $i = 1, ..., 5$ denote Monday through Friday, respectively. The five terms on the right-hand side of (7) are the covariances between each day in week t and the aggregated return of week $t + 1$; the five terms in (8) are the covariances between the aggregated return of week t and each day in week $t + 1$. The twenty-five terms in (9) are the pairwise covariances of the two weeks. These pairwise terms span different "orders" (lags): specifically, the lag is $h = 5 - i + j \in 1, ..., 9$. For example, the five covariances involving Monday of week t have orders 5, 6, 7, 8, and 9, whereas those involving Friday have orders 1, 2, 3, 4, and 5. If a different interval (e.g., Tue-Mon$^+$) is used to construct weekly returns, one obtains the same lag set $1, ..., 9$ but with a different composition of weekday pairs at each lag, which is what drives cross-interval differences when daily covariances are seasonal.

Autocovariances are useful for conveying econometric intuition, but for empirical implementation we report OLS-estimated coefficients from regression (1), consistent with the evidence on ρ in Section 2. Moreover,the volatilities of weekly (and daily) returns show no material seasonality (Table 1). Equations (7)–(9) provide three decompositions of the weekly ρ; Table 2 reports the corresponding estimated regression coefficients.[11]

Panels A–C in Part I report results for 1953–2024. In Panel A, regressing the next interval's return on each weekday's return shows, for example, that Monday negatively predicts Tue-Mon$^+$ (coefficient$= -0.073$, $t = -2.06$). That is, the return of Monday negatively predicts the return of the next interval, Tue-Mon$^+$, while Monday's coefficients for the other intervals are insignificant. Tuesday negatively predicts Mon$^+$-Fri$^+$ (-0.101, $t = -2.732$) but not the other intervals. Wednesday and Friday positively predict their corresponding following intervals—Thu-Wed$^+$ and Mon$^+$-Fri$^+$, respectively—whereas Thursday shows no predictive power. These patterns reveal substantial heterogeneity in the correlations between daily returns and subsequent weekly returns across interval definitions. Of the 25 coefficients, 6 are significant at the 10% level or better, indicating economically meaningful predictability of weekly returns by lagged daily returns.

Importantly, much of Panel A of Table 1 can be recovered from Panel A here via the decomposition in equation (7): averaging the five coefficients across weekdays for a given interval approximates the corresponding weekly AR(1). For instance, averaging the coeffi-

[11] Non-trading days are treated as missing observations.

cients in the Mon$^+$-Fri$^+$ row yields 0.001, close to the first ρ in Panel A of Table 1 (-0.001); the small gap reflects within-week day–day correlations. Likewise, averaging the Tue-Mon$^+$ row and the Tue$^+$-Mon$^+$+ row gives 0.055, which is close to the second ρ (0.043) in Panel A of Table 1.

Panel B reverses the conditioning: we regress each next-week daily return on the preceding week's return. For example, the coefficient of Mon-Fri on Mon$^+$ is 0.075 ($t = 8.568$), implying that the calendar-week return positively predicts the next Monday's return. By contrast, the Mon-Fri coefficients on Tue$^+$, Wed$^+$, and Thu$^+$ are all significantly negative, while the coefficient on Fri$^+$ is insignificant. Thus Mon-Fri significantly predicts four of five next-week daily returns, yet the calendar-week AR(1) in Table 1, Panel A, is insignificant because the positive and negative effects offset. Overall, 16 of the 25 coefficients in Panel B are statistically significant at the 10% level or better. Notably, across all interval definitions the weekly return consistently predicts Monday positively and Tuesday negatively. These results indicate pronounced seasonality in the correlations between weekly returns and following week's daily returns. As in Panel A, one can recover much of the weekly autocorrelations in Table 1, Panel A, by averaging across weekdays for a given interval, consistent with the decomposition in equation (8).

Panel C reports daily autocorrelations up to lag 9. The first column shows that Mon positively predicts Mon$^+$ (0.054, $t = 3.029$) but negatively predicts most other days, four of which are significant (Tue, Wed, Fri, Wed$^+$). Notably, the Mon$\rightarrow$Mon$^+$ coefficient ("$\rightarrow$" denotes the direction of prediction) is larger in magnitude than the Mon$\rightarrow$Wed/Thu/Fri coefficients, underscoring day-of-week seasonality. For Tue, correlations are positive for the next four days but negative for the following four. In particular, the Tue$\rightarrow$Mon^{++} coefficient is large and highly significant (0.08, $t = 3.969$), and much larger than Tue$\rightarrow$Mon$^+$ (0.008). Looking by destination day, the Mon$^+$ row contains five positive coefficients, three significant at the 1% level, whereas the Tue+ row contains five negatives. Of the 45 coefficients overall, 23 are positive and 27 are significant at the 10% level or better. Panels A and B can be largely recovered from Panel C via the decompositions in (7)–(9): averaging across the relevant columns or across the relevant rows. For example, the average of the Mon$^+$ row is 0.081, close to the Mon$^+$ coefficient in Panel B (0.075).

Parts II and III report results for the two subperiods. In each case, the decompositions align with the weekly AR(1) coefficients reported in Panels B and C of Table 1, respectively. Comparing corresponding panels across subperiods shows that day-of-week autocorrelation patterns have shifted markedly over time, consistent with the time-varying AR(1) in Table 1. For example, in Part II, Panel F (1953–1988), Mon$^+$ is positively correlated with nearly all prior-week days, whereas in Part III, Panel I (1989–2024) only Thu and Fri remain positive, and at much smaller magnitudes. This pattern suggests that the strong Monday "momentum" evident before 1989 has largely dissipated in recent decades. As another example, Mon→Tue is weakly positive in Part II, Panel F (0.024, t = 1.321) but strongly negative in Part III, Panel I (−0.17, t = −8.032), indicating a Tuesday reversal following Monday in the later subperiod versus insignificant momentum in the earlier one. Although we began by studying how interval choice affects the weekly AR(1), the evidence makes clear that a deeper investigation of day-of-week seasonality in daily autocorrelations is warranted.

3.3 Time Variation

The time-varying seasonality of daily autocorrelations documented in Parts II and III is consistent with the time-varying weekly AR(1) coefficient ρ across interval definitions in Table 1 (Panels B and C). Specifically, ρ is positive for every interval in 1953–1988 and negative for every interval in 1989–2024. To visualize the evolution of ρ more granularly, we estimate, for each interval, ρ in a 10-year rolling window updated annually, beginning with 1953–1962, and plot the results in Figure 1. Panel A shows substantial time variation and, regardless of interval definition, a downward trend: values are mostly positive early in the sample and mostly negative later. Despite these similarities, the paths differ across intervals.

For example, the Fri-Thu$^+$ series is the highest through 1973 but becomes the lowest after 2008. Thu-Wed$^+$ is persistently higher than the others, consistent with its highest ρ in Table 1, Panel A. By contrast, Tue-Mon$^+$ is often the lowest: it remains near zero until 1996 and then turns significantly negative, in line with the Tue-Mon$^+$ estimates in Table 1 (Panels A–C: -0.043, 0.011, -0.085). Panel B of Figure 1 (t-statistics) further indicates that, for most years, at least one interval exhibits a statistically significant AR(1) coefficient.

Panel C plots, over time, the cross-interval average of ρ and its range (the gap between the minimum and maximum across the five intervals), which gauges the strength of seasonality. The average ρ peaks around 1970, declines through 1980, peaks again in 1987, and then trends downward. It switches from positive to negative between 1996 and 1997 and has remained negative since, edging back toward zero after 2019. The range is wide in the first decade, peaking in 1970, narrows through 1979, and is relatively stable thereafter—except in 1997, when it nearly vanishes (0.02) before rebounding. Its highest post-1979 value occurs in 2021 (0.148). These patterns imply a persistent, though evolving, seasonality in ρ over time.

To quantify how interval-specific estimates of ρ co-move over time, Panel A of Table 3 reports pairwise correlations among the five rolling ρ series for the full sample and for each subsample. Over 1953–2024, all correlations are positive and exceed 0.60, indicating a strong common component. In subsamples, correlations are weaker and occasionally negative; in the later subsample (1989–2024), all but one remain positive. In the early subsample, the correlation between Tue-Mon$^+$ and Wed-Tue$^+$ is -0.436, suggesting divergence between these interval definitions.

Part II reports correlations of changes in ρ ($\Delta\rho$). For the full sample (Panel D), all correlations are positive, again consistent with a common trend. Subsample results differ: two pairs are negative in the early subsample, whereas none are negative in the later subsample; moreover, many correlations in the later subsample (Panel F) are larger than in the full sample (Panel D). The rise in cross-interval correlations over time points to convergence in the seasonality of weekly return autocorrelations across interval definitions. That said, seasonality has not vanished: several correlations remain low, and Figure 1 shows mild re-divergence near the end of the sample.

Table 2 can also recover back-of-the-envelope estimates of the daily AR(1) abstracting from seasonality. In Panel C of Part I, the top entry in each column is the correlation between consecutive weekdays (treating Fri and Mon$^+$ as consecutive). Averaging these five values yields 0.047, close to the daily AR(1) estimate for 1953–2024 of 0.034 ($t = 4.617$).[12] Applying the same averaging to Panel F of Part II and Panel I of Part III for the subsamples gives 0.258 and −0.042, respectively—reasonably close to the corresponding AR(1) estimates of 0.195 ($t = 18.886$) and −0.047 ($t = -4.487$).

4 Further Analyses

4.1 Potential Mechanisms

Hu, Jin, and Wang (2025) group existing explanations for time-varying daily AR(1) into four categories: nonsynchronous trading; sluggish response to information; time-varying expected returns; and liquidity. Since these theories do not, on their own, generate the cross-interval weekly AR(1) patterns and day-of-week autocorrelation seasonality we find, we posit that seasonality in trading—potentially interacting with microstructure frictions—is an underlying driver, consistent with but not proving a causal link.

For example, traders may behave differently around the weekend. With heightened un-

[12] The average is an approximation and contains error. One source of error is the treatment of nontrading days. The daily AR(1) is estimated from $r_t = \mu + \rho r_{t-1} + \varepsilon_t$, where the $(t-1, t)$ observations need not be consecutive trading days. For example, if Mon$^+$ is a is a holiday, then Tue$^+$ is the $t+1$ observation for Fri. The product of this (Fri, Tue$^+$) pair contributes to the second-order autocorrelation in Table 2, not to the five adjacent-day coefficients we average. Hence the simple average omits skip-day pairs and differs from the regression-based AR(1).

certainty over the nontrading window, investors can underreact to news on Friday (and even Thursday), with the delayed adjustment spilling into Monday. This generates a Monday momentum effect as the market incorporates lagged information. The significantly positive Thu→Mon$^+$ and Fri→Mon$^+$ coefficients in Table 2 (Panels C, F, and I) are consistent with this mechanism.

The underreaction story, however, struggles to account for the positive Mon→Mon$^+$, Tue→Mon$^+$, and Wed→Mon$^+$ coefficients in Panel F (1953–1988), which would imply underreaction persisting through the entire week. This evidence can be reconciled if trading behavior has evolved with market structure and technology. In earlier decades, investors may have underreacted more broadly, with information arriving during the week incorporated only by the following Monday. Consistent with this interpretation, in 1989–2024 the Thu→Mon$^+$ and Fri→Mon$^+$ coefficients are much smaller—and often only marginally significant—than in 1953–1988, suggesting a diminishing Monday-momentum effect as trading technology and market efficiency improved.

In contrast to Monday's momentum, Tuesday exhibits reversal. In 1953–1988, the Monday–Tuesday correlation (0.024, $t = 1.321$) is the smallest and least significant among the five adjacent weekday pairs; in 1989–2024, it becomes the most strongly negative (-0.17, $t = -8.032$). Tuesday is also negatively correlated with the prior Thursday and Friday, in contrast to Monday's positive correlations with those days. The Tuesday reversal in the later subperiod is large enough to offset Monday momentum, helping explain why the AR(1) for Mon-Fri is significantly negative in 1989–2024 (-0.061, $t = -2.658$). It also helps rationalize the significantly negative AR(1) for Tue–Mon$^+$ (-0.085, $t = -3.671$): the next-week return under Tue–Mon$^+$ includes Tue$^+$, which is negatively correlated with Mon$^+$, Fri, and Thu from the preceding interval. One interpretation is that Tuesday's reversal corrects earlier overreaction.

Panel C of Figure 1 suggests historical episodes that may have shaped autocorrelations through changes in technology and market efficiency. The elevated AR(1) levels in the 1960s coincided with a surge in trading volume while trading technology lagged.[13] The cross-interval average AR(1) peaked in the early 1970s and then declined into the early 1980s. Notably, this post-1970 decade saw the launch of NASDAQ and the CBOE options exchange, the adoption of SEC Rule 19b-3 ending fixed commissions, the advent of electronic trading, and the rise of indexing. From the early 1980s, the average weekly AR(1) rose again, peaking in 1987 and then easing, against the backdrop of a bull market culminating in Black Monday (October 19, 1987). This period also featured the introduction of stock-index futures and options and the growth of program trading; a common view holds that program trading and index arbitrage contributed to the 1987 crash. Beginning in 1997–1998, the average weekly AR(1) turned negative and has generally remained so. Alongside the Asian financial crisis and the 1998 Russian default, this period saw shrinking tick sizes and accelerating electronic trading. The cross-interval range of AR(1) reached its sample low in 1997. The years 2000 and 2008 mark local minima in the average weekly AR(1), aligning with the dot-com bust and the global financial crisis. After a trough in 2019, the average has increased toward zero, though not significantly, during the post-pandemic era amid rising retail market participation. These coincidences are suggestive rather than causal, but they are consistent with technology and market structure influencing return autocorrelations over time (e.g., Baltussen et al., 2019).

4.2 Tuesday Following Nontrading Monday

As a test of our trading-based interpretation of daily autocorrelation seasonality, we examine the subsample of trading Tuesdays that follow nontrading Mondays.[14] If trading were

[13] During June–December 1968, the overload culminated in the "paperwork crisis," and the NYSE instituted midweek (Wednesday) closures.

[14] Although the procedure applies to any weekday, Tuesdays provide the most observations. This test parallels Bessembinder and Hertzel (1993), who analyze AR(1) near nontrading days such as Mondays and holidays.

irrelevant, autocorrelations involving these Tuesdays would not differ from those involving regular Tuesdays. If trading matters, we expect differences, because these Tuesdays are the first—rather than the second—trading day of the week, and Table 2 shows substantial Monday–Tuesday differences in autocorrelations.

To illustrate, Table 4 reports—by subsample—the correlation coefficients between the Tuesday return and lead/lag weekly returns. In Panel A, we use the Tuesday return to predict future weekly returns; its columns should be compared with the corresponding Tuesday columns in Panels A, D, and G of Table 2, respectively. The Panel A results differ markedly from those in Table 2. For 1953–2024, all coefficients in Panel A are positive—two are significant at the 10% level or better—whereas the corresponding entries in Panel A of Table 2 are mixed in sign, including one that is significantly negative at the 1% level.

In Panel B, for ease of presentation we regress the Tuesday return on lagged weekly returns. This is equivalent to using weekly returns to predict the subsequent Tuesday return. For comparison, each column of Panel B should be read against the corresponding entries in the Tue^{+} and Tue^{++} rows of Table 2 (Panels B, E, and H). For example, the first coefficient in Panel B—the regression of Tue on Tue^{-}-Mon, is 0.061 ($t = 1.595$), whereas the corresponding value in Panel B of Table 2 (first entry in the Tue-Mon^{+} column) is -0.015 ($t = -1.873$); a simple difference test indicates these coefficients differ significantly. In the 1953–1988 subsample (Panel B), all but one coefficient are positive, albeit statistically insignificant, whereas the five corresponding coefficients in Panel E of Table 2 are all negative, four significant at the 10% level or better. By contrast, the Mon coefficients in Panel E of Table 2 are uniformly and significantly positive, suggesting that Tuesdays following nontrading Mondays inherit the "missing Monday" effect. The insignificantly positive coefficients in Panel B for 1953–1988 likely reflect offsetting influences from positive coefficients for trading Mondays and negative coefficients for regular Tuesdays. Taken together, evidence from the subsample of Tuesdays after nontrading Mondays supports our claim that seasonality in trading is a plausible driver of the documented seasonality in daily autocorrelations.

4.3 Daily Autocorrelations Over Time

While Figure 1 shows time variation in AR(1) for weekly returns across interval definitions, Figure 2 drills down to the underlying day-level dynamics. It plots ten-year rolling estimates of daily autocorrelations at lags 1–9. For each rolling window and lag n, we estimate the nth-order autocorrelation by OLS:

$$r_{t+n} = \mu_n + \rho_n r_t + \varepsilon_{t+n}. \tag{10}$$

In each panel, we plot ρ_n of five weekday-specific subsamples of r_t corresponding to the five destination weekdays, respectively.[15] The rolling-window plots of daily autocorrelations confirm the full-sample and subsample results in Table 2. In Panel A (AR(1)), the thin solid line (Fri→Mon$^+$) is positive for most of the sample (turning down only near the end) and is almost always above the other paths. By contrast, the thick solid line (Mon→Tue) is mostly negative except during 1970–1986 and is typically the lowest. The AR(1) series for Tue→Wed, Wed→Thu, and Thu→Fri tend to move together, albeit not in lockstep. Panel B shows pronounced swings in AR(2) across weekdays. For higher orders as well, several weekday pairs exhibit sizable AR(n) coefficients with substantial time variation.

Figure 3 plots the cross-interval average and range of the daily autocorrelations from Figure 2. In Panel A, the average AR(1) coefficient rises initially, peaks in 1972, then declines steadily, crossing zero in 2008 and reaching a low of -0.135 in 2021.[16] The AR(1) range (max–min across weekdays) fluctuates over time—narrowing early, widening around 1987, and then shrinking to a relatively stable level after 1997. In Panel B, the average AR(2) is near zero for almost the entire sample, except the last five years. Its range follows dynamics similar to AR(1). In later years, the average AR(6), AR(7), and AR(9) are positive, whereas

[15] For example, if we estimate ρ_1 for the Monday subsample using the full sample rather than a 10-year window, the estimate coincides with the first entry in the Mon column of Table 2, Panel C.

[16] The shift in the daily AR(1) from positive to negative has been documented by Baltussen, van Bekkum, and Da (2019), Lewellen (2022), Bogousslavsky, LeBaron, and Pontiff (2025), and Hu, Jin, and Wang (2025).

the average AR(8) is negative. Across orders, the ranges exhibit pronounced time variation. Even when the average is near zero, a large range indicates sizable AR coefficients for some weekday subsamples.

Table 5 reports summary statistics for the nine "range" series associated with daily autocorrelations at lags 1–9. Low-order ranges are generally larger than high-order ranges, with higher means and maxima. On average, the standard deviation is about 43% of the average range across the nine lags, indicating substantial time variation, and the average first-order autocorrelation of the ranges is roughly 0.8, indicating persistence. The cross-correlations show a clear structure: the first five ranges are almost always positively correlated (except for the correlation between lags 4 and 5, −0.068); the first five are mostly negatively correlated with the sixth–ninth ranges; and the sixth–ninth ranges are all positively correlated with one another. Thus, high-order ranges tend to move opposite to low-order ranges. This pattern accords with Figure 3, where ranges for lags 1–4 are elevated early in the sample, whereas ranges for lags 6–9 are elevated in recent years. Overall, these results underscore the intricate, time-varying nature of day-of-week seasonality in daily autocorrelations.

4.4 Asymmetry in Daily Autocorrelations

Hu, Jin, and Wang (2025) a systematic sign asymmetry in the daily AR(1): return reversals are more likely following negative returns. We ask whether this asymmetry extends to higher-order autocorrelations and varies by weekday. Specifically, we test for day-of-week seasonality in the sign-conditional coefficients ρ_n^- and ρ_n^+, obtained by estimating regression (10) on the subsamples with $r_t < 0$ and $r_t \geq 0$, respectively.

Table 6 reports OLS estimates of the sign-conditional autocorrelations ρ_n^- and ρ_n^+ for each weekday up to lag 9 over 1953–2024 and for the two subsamples. Panels A and B show that ρ_n^- and ρ_n^+ can differ markedly. For example, for Mon→Tue, ρ_1^- is significantly negative (−0.204, $t = -8.574$), whereas the corresponding ρ_1^+ is insignificant (−0.027, $t = -0.952$). Together with the average Mon→Tue coefficient in Panel C of Table 2 (-0.092, $t = -6.492$), this contrast indicates that the Tuesday reversal is concentrated following negative Mondays. As a second example, six of the nine ρ_n^- for Wed are significant, but only two of the corresponding ρ_n^+ are significant; in contrast, for Fri only three ρ_n^- are significant, whereas eight ρ_n^+ are significant. These results highlight pronounced sign asymmetry that varies by weekday and lag.

Parts II and III (1953–1988; 1989–2024) show that the asymmetry in daily autocorrelations is time-varying. For Monday at lag 2, ρ_2^- and ρ_2^+ are -0.285 ($t = -10.451$) and 0.237 ($t = 4.694$) in 1953–1988, but 0.12 ($t = 3.188$) and -0.07 ($t = -1.79$) in 1989–2024—both smaller in magnitude and with flipped signs. Focusing on the later subperiod (Part III), the Tuesday (Wednesday) reversal is concentrated following negative Monday (Tuesday) returns. These granular results complement the baseline AR(1) asymmetry documented by Hu, Jin, and Wang (2025).

4.5 Monthly Interval

The dependence of the AR(1) coefficient on the interval choice is not confined to the weekly frequency. We extend the analysis to monthly intervals and accommodate unequal month lengths as follows. Define 31 interval definitions, anchored on calendar days $d = 1, \ldots, 31$. For a given month, the d-anchored interval begins on day d and ends on the day before day d of the next calendar month (e.g., May 10–June 9). If the start (end) day does not exist, we substitute the closest following (previous) available day. For instance, the 31st interval for April begins on May 1 (there is no April 31) and ends on May 30; the 31st interval for January of a non-leap year is January 31–February 28. We denote these as M1,M2,...,M31, with the calendar month corresponding to M1 (day 1 to the day before day 1 of the next month).

For each interval, we construct the corresponding "monthly" return by summing the daily log returns within that interval. Figure 4 plots OLS estimates of the AR(1) coefficient (ρ) across interval definitions. To increase power, we use 1926–2024 as the full sample and 1926–1974 and 1974–2024 as two subsamples. For brevity, Table 7 reports the results of Mo1, Mo4, Mo7, ..., Mo28, Mo31.

The solid line for 1926–2024 in Figure 4 shows that ρ is positive for all interval definitions and follows a U-shaped pattern, with a minimum around Mo8–Mo10 and maxima near the turn of the month. Thus, when estimating the first-order autocorrelation of monthly returns over the full sample, a researcher would obtain significantly positive estimates if the interval begins in the first or last few days of the month. For example, for the calendar month (Mo1) in Table 7, Panel A, $\rho = 0.088$ ($t = 3.042$). By contrast, for an interval such as Mo10 (starting on the 10th), ρ is essentially zero (0.013, $t = 0.457$). These results echo our weekly findings: the AR(1) of time-aggregated returns depends on the interval definition.

The two subsamples are similar in some respects and different in others. In particular, for any interval, the 1926–1974 estimate of ρ is larger and more significant than the 1975–2024 estimate, so the full-sample estimate is roughly the midpoint of the two. In 1975–2024, all interval-specific estimates are insignificant and about half are negative. Notably, a U-shaped cross-interval profile of ρ remains visible in 1975–2024. Although individual ρ estimates are weak in that period, the spread between the maximum (Mo2) and minimum (Mo10) is about the same magnitude as the spread between Mo29 (maximum) and Mo11 (minimum) in 1926–1974. To test whether the Mo2–Mo10 difference in 1975–2024 is statistically significant, we estimate an augmented pooled AR(1) regression by combining the Mo2 and Mo10 samples:

$$r_t = \mu + \gamma I_{t-1} + \rho r_{t-1} + \delta I_{t-1} r_{t-1} + \epsilon_t, \tag{11}$$

where I is a dummy variable that equals one for Mo2 and otherwise. The estimate of ρ is -0.057 and insignificant ($t = -1.428$), whereas the interaction δ is 0.103 ($t = 1.795$), statistically significant at the 10% level. This implies a positive difference between the AR(1) coefficients of Mo2 and Mo10.[17]

Table 7 also reports distributional statistics (skewness and kurtosis). For the full sample (Panel A), Mo13 has the most negative skewness (-1.154) and the highest kurtosis (16.222) across intervals. The same pattern holds in the first subsample. In the second subsample, however, Mo28 exhibits the most negative skewness (-1.970) and the highest kurtosis (14.529). Consistent with our weekly results, the skewness and kurtosis of monthly returns—like ρ—depend not only on the interval definition but also on the sample period.

The seasonality in monthly AR(1) coefficients across interval definitions may also reflect investor underreaction/overreaction and liquidity effects, as in the weekly results. Although monthly data lack an explicit nontrading-weekend gap, investors may behave differently at the turn of the month versus mid-month. Regularly timed institutional activities—such as portfolio rebalancing, window dressing, and contribution- or payroll-driven fund flows—could plausibly contribute to the observed seasonality. We view these mechanisms as consistent with, rather than definitive causes of, the evidence.

4.6 Weekly AR(1) Coefficient and Within-Month Timing

The U-shaped cross-interval pattern in monthly AR(1) echoes our earlier finding that weekly AR(1) variation across intervals is driven by day-of-week seasonality in daily autocorrelations. In unreported calculations, aggregating daily autocorrelations within each monthly interval reproduces the monthly AR(1) profile.[18] A natural next step is to study how weekly and monthly seasonality interact: are weekly AR(1) patterns more pronounced at the beginning, middle, or end of the month? We address this by classifying each week into four

[17] In both the first subsample and the full sample, the maximum and minimum ρ occur at Mo29 and Mo11, respectively. The estimated δ from regression (11) is 0.131 ($t = 2.236$) for 1926–1974 and 0.089 ($t = 2.171$)for 1926–2024, both statistically significant at the 5% level.

[18] Because months have unequal lengths, there is no direct monthly analogue to Panel C of Table 2 (daily autocorrelations). Instead, we partition each month into within-month groups of roughly equal length—akin to the quarterly decomposition described below—and examine the autocorrelations of group-level returns.

within-month positions (Q1–Q4) based on its start day and re-estimating weekly AR(1) by interval×position. This design reveals where within the month the weekly effects concentrate and how that concentration shifts over time.

Because weeks and months do not align, we approximate a week's position within a calendar month by labeling each weekly interval with a within-month "quarter" (Q1–Q4) based on the calendar day of its last trading day. Concretely, we assign the week to the month containing its last day, and then define: Q1 if last day ≤ 7; Q2 if not Q1 and last day ≤ 15; Q3 if not Q1–Q2 and last day ≤ 24; and Q4 otherwise. By construction, Q2–Q4 lie entirely within the month, whereas Q1 may overlap the previous month. Across the sample, quarters Q1–Q4 account for approximately 23%, 26%, 29%, and 22% of weekly intervals, respectively.

We estimate ρ from regression (1) conditional on a week's position within the month in two ways. First, we restrict the sample so that the regressor week (t) lies in a designated within-month quarter (e.g., Q1). Second, we restrict the sample so that the dependent week ($t + 1$) lies in that quarter. Table 8 reports OLS estimates of ρ under both conditioning schemes for each weekly interval definition and sample period.

As shown in Part I, Panel A (full sample) and conditioning on the location of r_t, the estimated ρ varies markedly across the five interval definitions and the four within-month quarters. In the second quarter (Q2), ρ is positive for every interval and significant for two; in the fourth quarter (Q4), ρ is always negative and significant for all but one interval. Thus, weekly AR(1) switches sign within the month—positive in the middle, negative at month-end. Panels B and C indicate that the mid-month positive AR(1) is more pronounced in 1953–1988, whereas the end-month negative AR(1) is more pronounced in 1989–2024. The third quarter (Q3) is significantly positive in the first subperiod but significantly negative in the second, rendering it mostly insignificant in the full sample.

It is informative to compare Table 8 with Table 1, which does not condition on a week's within-month location. Over 1953–2024, the unconditional ρ is significant only for Tue-Mon$^+$. By contrast, conditioning on the location of the weekly interval yields significant ρ for multiple interval definitions in specific quarters. This contrast underscores the interaction between weekly- and monthly-frequency seasonality.

Part II reports the corresponding results when we condition on the location of r_{t+1}. Because the four quarters are roughly equal in size, the patterns mirror Part I after a cyclic relabeling of quarters (Q1→Q2, Q2→Q3, Q3→Q4, Q4→Q1). Panel E indicates that in 1953–1988 weekly returns in Q3 and Q4 are highly predictable with positive coefficients, whereas Panel F shows that in 1989–2024 weekly returns in Q1 and Q4 are highly predictable but with negative coefficients.

4.7 International Stock Markets

Are our findings unique to the US market? We address this by extending the baseline analysis to eight international markets.[19] We obtain daily stock-index returns for Australia, Denmark, Hong Kong, Japan, Singapore, Sweden, Switzerland, and the United Kingdom from WRDS World Indices. The WRDS series are available from July 1, 1986 to June 30, 2025; we use 1989–2024 (1/1/1989–12/31/2024) to align with the U.S. (CRSP) subsample analyzed earlier. Additional markets in WRDS—such as Germany and France—are excluded due to shorter coverage over this window.

Table 9 reports AR(1) coefficients for weekly returns across interval definitions, along with skewness and kurtosis. For Australia, the Tue-Mon$^+$ and Wed-Tue$^+$ coefficients (-0.04, $t = -1.714$; -0.05, $t = -2.161$) are significantly negative at the 10% level and 5% level, while the other three intervals are positive but insignificant. Notably, the calendar-week coefficient is insignificant in all eight markets. In every market except Denmark, at least one interval exhibits a significantly negative AR(1) at the 10% level; in particular, Tue-Mon$^+$ is

[19] Additional results for these markets are omitted for brevity but are available upon request.

significantly negative in six of the eight markets. With the exception of Singapore's Thu-Wed$^+$ and Fri-Thu$^+$, all significant coefficients are negative.These predominantly negative AR(1) estimates resemble the U.S. results in Table 1, Panel C, and are consistent with seasonality in daily autocorrelations.

Skewness and kurtosis display seasonal patterns as well. For Australia, Denmark, Sweden, Switzerland, and the U.K., both moments are larger for Mon-Fri and Fri-Thu$^+$. In Hong Kong and Singapore, they are largest for Tue-Mon$^+$, whereas for Japan they are relatively flat across intervals. A common feature across all eight markets is that skewness and kurtosis for Wed-Tue$^+$ and Thu-Wed$^+$ are low relative to other intervals—also observed for the U.S. in Table 1, Panel C. These results suggest commonalities in seasonality across markets, plausibly reflecting increasing global integration, though this interpretation is suggestive rather than causal.

To explain the seasonal patterns in weekly AR(1) coefficients across interval definitions, Table 10 reports daily autocorrelations up to lag 9 for the eight international markets. As with the U.S., suitable averages of these daily autocorrelations closely approximate the AR(1) coefficients in Table 9. Denmark and Sweden have the fewest significant daily autocorrelations (13 each), while Japan has the most (24). Consistent with the U.S. evidence (Table 6, Panel I), the Fri$\rightarrow$Mon$^+$ coefficient is significantly positive in all markets except Australia, and the Mon$\rightarrow$Tue coefficient is significantly negative in all markets except Denmark and Sweden. Other weekday pairs vary by market and are sometimes difficult to interpret. For example, only in Japan and Sweden are the first seven Mon$\rightarrow \cdot$ coefficients negative; Japan also exhibits many significantly positive coefficients (ten) for other weekdays. In Australia, several ninth-order terms (Mon$\rightarrow$Fri$^+$, Thu$\rightarrow$Wed^{++}, and Fri$\rightarrow$Thu^{++}) are significant. Overall, the evidence points to pervasive seasonality in daily autocorrelations across all eight international markets.

5 Conclusion

While calendar intervals are the standard choice for temporally aggregating daily stock returns, other definitions are also used in practice. We show that interval choice affects the AR(1) of aggregated returns when daily autocorrelations exhibit seasonality. We document substantial cross-interval variation in weekly AR(1) coefficients and demonstrate day-of-week seasonality in daily autocorrelations consistent with these patterns. Diagnostic evidence suggests that seasonality in trading activity is a likely driver, and that its evolution over time reflects changes in market structure and technology. Finally, the time-varying sign asymmetry in daily autocorrelations and the interaction between weekly- and monthly-frequency seasonality motivate further investigation into the dynamics of stock returns.

References

Abraham, Abraham, and David L. Ikenberry, 1994, The individual investor and the weekend effect, *The Journal of Financial and Quantitative Analysis* 29, 263–277.

Ahn, Dong-Hyun, Jacob Boudoukh, Matthew Richardson, and Robert F. Whitelaw, 2002, Partial adjustment or stale prices? Implications from stock index and futures return autocorrelations, *The Review of Financial Studies* 15, 655–689.

Ariel, Robert A., 1987, A monthly effect in stock returns, *Journal of Financial Economics* 18, 161–174.

Atchison, Michael D., Kirt C. Butler, and Richard R. Simonds, 1987, Nonsynchronous security trading and market index autocorrelation, *The Journal of Finance* 42, 111–118.

Baltussen, Guido, Sjoerd van Bekkum, and Zhi Da, 2019, Indexing and stock market serial dependence around the world, *Journal of Financial Economics* 132, 26–48.

Bessembinder, Hendrik, and Michael G. Hertzel, 1993, Return autocorrelations around non-trading days, *The Review of Financial Studies* 6, 155–189.

Bogousslavsky, Vincent, Blake D. LeBaron, and Jeffrey Pontiff, 2025, A century of market reversals: Resurrecting volatility, https://ssrn.com/abstract=5410662.

Bondarenko, Oleg, 2014, Variance trading and market price of variance risk, *Journal of Econometrics* 180, 81–97.

Boudoukh, Jacob, Matthew P. Richardson, and Robert F. Whitelaw, 1994, A tale of three schools: Insights on autocorrelations of short-horizon stock returns, *The Review of Financial Studies* 7, 539–573.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *The Quarterly Journal of Economics* 108, 905–939.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press, Princeton, NJ).

Chang, Eric C., J. Michael Pinegar, and R. Ravichandran, 1993, International evidence on the robustness of the day-of-the-week effect, *Journal of Financial and Quantitative Analysis* 28, 497–513.

Chen, Honghui, and Vijay Singal, 2003, Role of speculative short sales in price formation: The case of the weekend effect, *The Journal of Finance* 58, 685–705.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, *The Journal of Finance* 55, 913–935.

Cohen, Kalman J., Gabriel A. Hawawini, Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1983a, Estimating and adjusting for the intervalling-effect bias in beta, *Management Science* 29, 135–148.

Cohen, Kalman J., Gabriel A. Hawawini, Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1983b, Friction in the trading process and the estimation of systematic risk, *Journal of Financial Economics* 12, 263–278.

Connolly, Robert A., 1989, An examination of the robustness of the weekend effect, *Journal of Financial and Quantitative Analysis* 24, 133–169.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

French, Kenneth R., 1980, Stock returns and the weekend effect, *Journal of Financial Economics* 8, 55–69.

Gibbons, Michael R., and Patrick Hess, 1981, Day of the week effects and asset returns, *The Journal of Business* 54, 579–596.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, *The Review of Financial Studies* 20, 1113–1138.

Hu, Grace Xing, Zhao Jin, and Jiang Wang, 2025, Autocorrelation in daily stock market returns: Time-variation and asymmetry, https://ssrn.com/abstract=5314371.

Jaffe, Jeffrey F., and Randolph Westerfield, 1985, The week-end effect in common stock returns: The international evidence, *The Journal of Finance* 40, 433–454.

Keim, Donald B., and Robert F. Stambaugh, 1984, A further investigation of the weekend effect in stock returns, *The Journal of Finance* 39, 819–835.

Kole, Erik, Thijs Markwat, Anne Opschoor, and Dick van Dijk, 2017, Forecasting value-at-risk under temporal and portfolio aggregation, *Journal of Financial Econometrics* 15, 649–677.

Lakonishok, Josef, and Seymour Smidt, 1988, Are seasonal anomalies real? A ninety-year perspective, *The Review of Financial Studies* 1, 403–425.

Lewellen, Jonathan, 2022, Autocorrelation of stock and bond returns, 1960–2019, Dartmouth College Working Paper.

Lo, Andrew W., and A. Craig MacKinlay, 1990, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181–211.

Lo, Andrew W., and A. Craig MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *The Review of Financial Studies* 1, 41–66.

Mech, Timothy S., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307–344.

Neuberger, Anthony, 2012, Realized skewness, *The Review of Financial Studies* 25, 3423–3455.

Ogden, Joseph P., 1990, Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects, *The Journal of Finance* 45, 1259–1272.

Scholes, Myron, and Joseph Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics* 5, 309–327.

Silvestrini, Andrea, and David Veredas, 2008, Temporal aggregation of univariate and multivariate time series models: A survey, *Journal of Economic Surveys* 22, 458–497.

Figure 1: AR(1) Coefficients for Weekly Intervals

This figure plots the OLS-estimated AR(1) coefficient (ρ) and corresponding t-statistics for weekly log returns on the VW CRSP index over 1953–2024, using five weekly interval definitions: Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$. Estimates use a ten-year rolling window updated annually, beginning with 1953–1962. Panels A reports ρ; Panel B reports the associated t-statistics, with dotted horizontal lines marking the 95% confidence thresholds. Panel C, shows, across the five intervals, the cross-interval average of ρ (solid line), the minimum and maximum (dotted lines), and the range (maximum–minimum, dashed line).

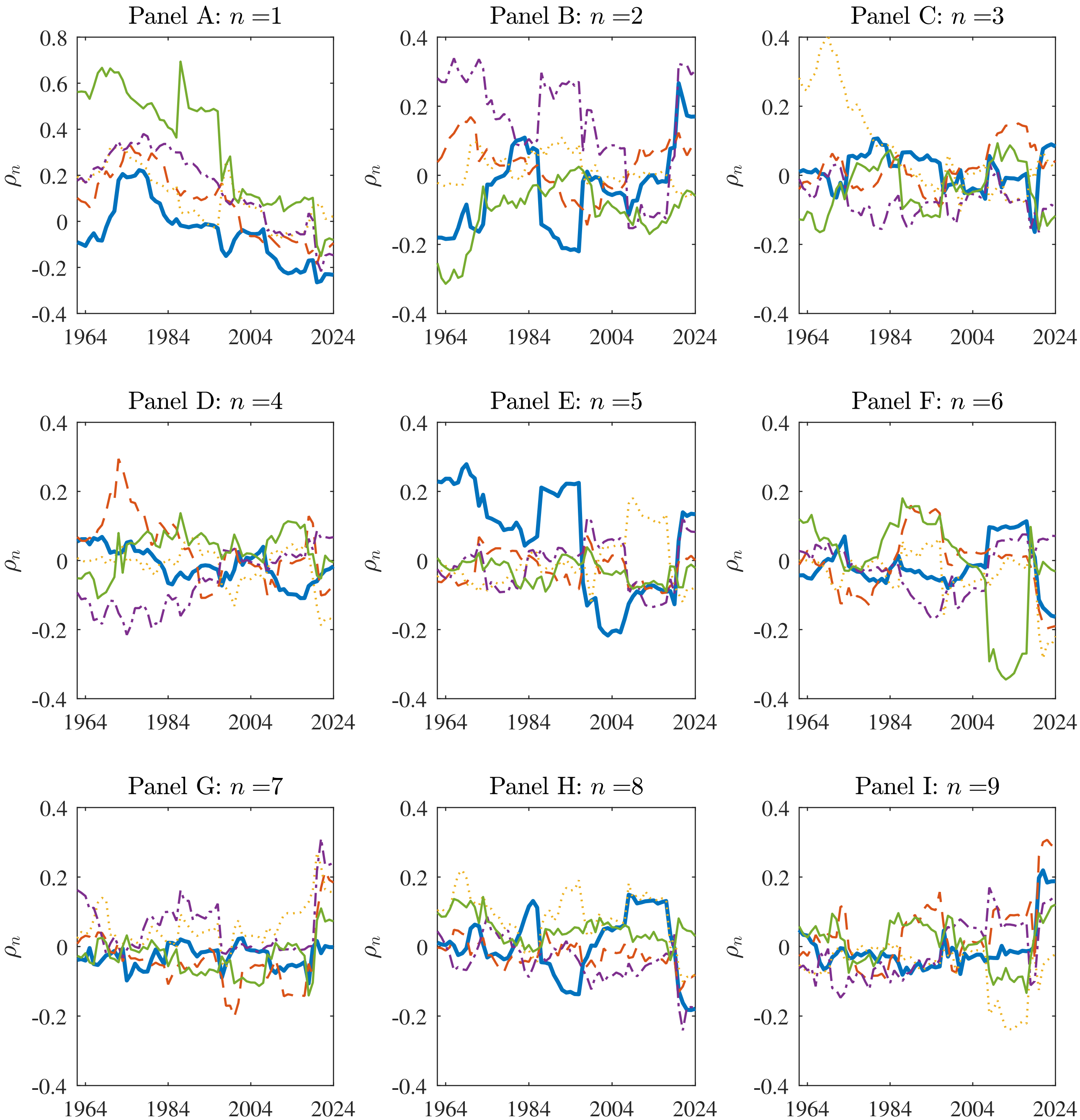

Figure 2: Daily Autocorrelations for Different Weekdays

This figure plots OLS estimates of daily autocorrelations up to the ninth order for log returns on the VW CRSP index over 1953–2024, using a 10-year rolling window updated annually (starting 1953–1962). Panels A–I correspond to lags 1–9, respectively. For each lag n, we estimate $r_{t+n} = \mu_n + \rho_n r_t + \varepsilon_{t+n}$ and plot estimates of ρ_n from five weekday-specific subsamples of r_t. Line styles denote destination weekday in each panel: Monday (thick solid), Tuesday (dashed), Wednesday (dotted), Thursday (dot–dashed), Friday (thin solid).

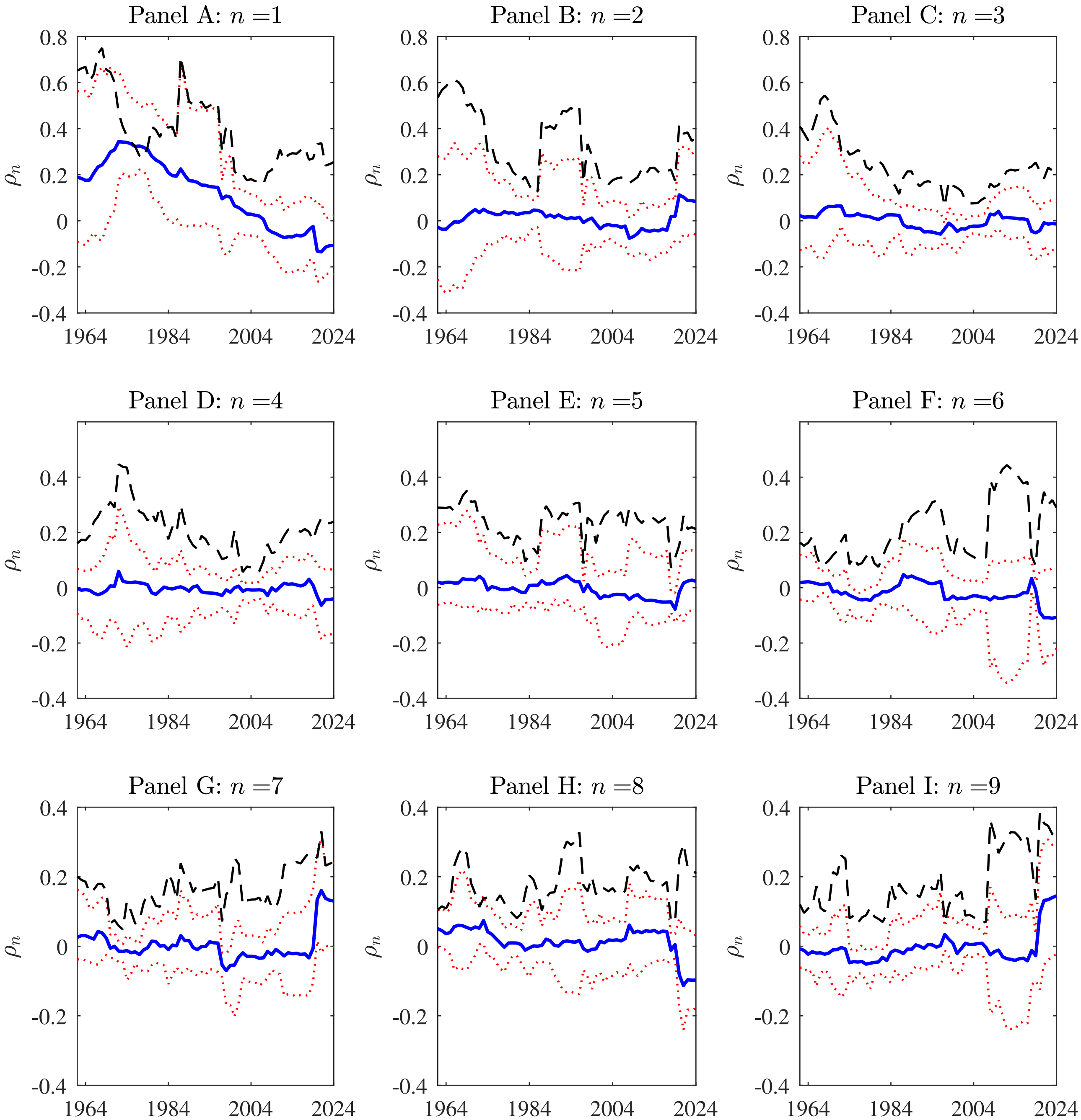

Figure 3: Average and Range of Daily Autocorrelations for Different Weekdays

This figure plots, for the five weekday-specific subsamples of r_t, the average and range of daily autocorrelations up to the ninth order for VW CRSP log returns over 1953–2024. Estimates use 10-year rolling windows updated annually (starting 1953–1962). Panels A–I correspond to lags 1–9, respectively. For each lag n, we estimate $r_{t+n} = \mu_n + \rho_n r_t + \varepsilon_{t+n}$and compute the cross-weekday mean and range of ρ_n. The thick solid line is the mean; dotted lines show the minimum and maximum across weekdays; the dashed line is the range (maximum–minimum).

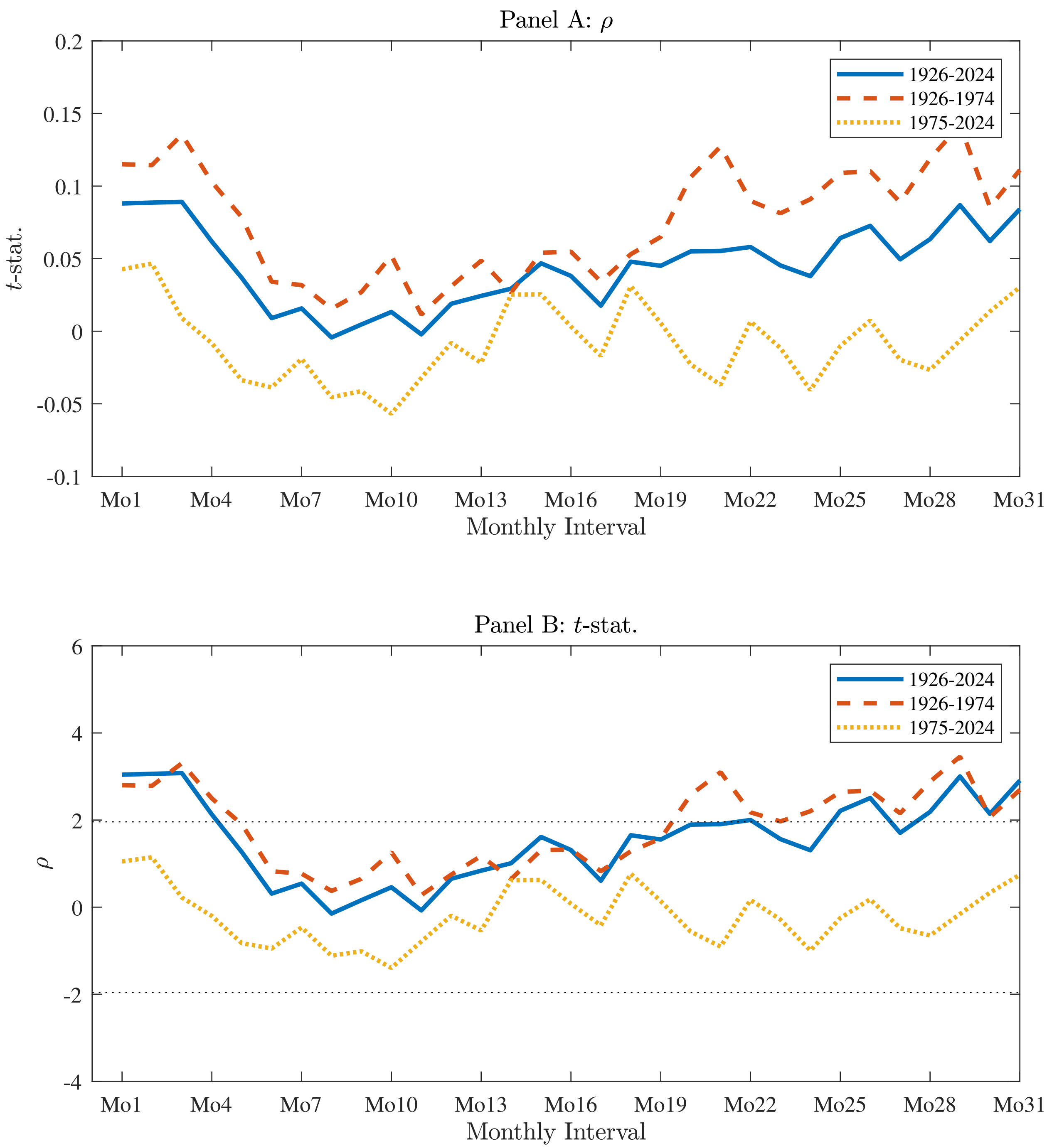

Figure 4: AR(1) Coefficients for Monthly Intervals

This figure plots OLS estimates of the AR(1) coefficient (ρ) and corresponding t-statistics for monthly log returns on the VW CRSP index over 1926–2024 and for two subsamples. Monthly interval definitions begin on calendar days 1–31 and end on the day before the same day of the following month (e.g., May 10–June 9); when a start (end) day does not exist, the next (previous) available day is used. Panel A reports ρ; Panel B reports the associated t-statistics, with dotted horizontal lines marking the 95% confidence thresholds.

Table 1: AR(1) Coefficients for Different Weekly Intervals

This table reports, for each weekly interval, OLS estimates of the AR(1) coefficient (ρ) and its t-statistic for weekly log returns on the VW CRSP index over multiple periods. We also report the mean (%) and standard deviation (%) of returns, as well as skewness and kurtosis. The five interval definitions are Mon-Fri (Mon-Sat before 1953), Tue-Mon^{+}, Wed-Tue^{+}, Thu-Wed^{+}, and Fri-Thu^{+}, where "$^{+}$" denotes the following calendar week. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Interval	ρ	t-stat.	Mean	St.Dev.	Skew.	Kurt.
			Panel A: 1953–2024			
Mon-Fri	−0.001	−0.055	0.197	2.128	−0.793	10.239
Tue-Mon^{+}	-0.043^{***}	−2.658	0.198	2.308	−0.866	12.972
Wed-Tue^{+}	−0.012	−0.733	0.198	2.159	−1.118	14.211
Thu-Wed^{+}	0.021	1.273	0.196	2.104	−0.883	8.950
Fri-Thu^{+}	−0.017	−1.020	0.197	2.137	−1.141	14.393
			Panel B: 1953–1988			
Mon-Fri	0.090^{***}	3.925	0.200	1.895	−0.533	7.623
Tue-Mon^{+}	0.011	0.462	0.200	2.146	−1.297	19.282
Wed-Tue^{+}	0.047^{**}	2.038	0.200	2.046	−1.431	23.138
Thu-Wed^{+}	0.111^{***}	4.819	0.199	1.899	−0.666	8.325
Fri-Thu^{+}	0.094^{***}	4.095	0.200	1.917	−0.757	9.736
			Panel C: 1989–2024			
Mon-Fri	-0.061^{***}	−2.658	0.194	2.339	−0.911	10.757
Tue-Mon^{+}	-0.085^{***}	−3.671	0.196	2.460	−0.570	8.951
Wed-Tue^{+}	-0.060^{***}	−2.607	0.197	2.266	−0.879	8.039
Thu-Wed^{+}	-0.041^{*}	−1.771	0.193	2.292	−0.987	8.800
Fri-Thu^{+}	-0.091^{***}	−3.984	0.194	2.338	−1.327	15.718
			Panel D: 1926–2024			
Mon-Sat	0.016	1.151	0.182	2.462	−0.665	10.864
Tue-Mon^{+}	−0.015	−1.066	0.183	2.613	−0.683	12.238
Wed-Tue^{+}	0.006	0.448	0.183	2.508	−1.221	17.894
Thu-Wed^{+}	0.044^{***}	3.173	0.179	2.438	−0.776	10.757
Fri-Thu^{+}	0.027^{*}	1.913	0.179	2.420	−0.861	11.826
			Panel E: 1926–1974			
Mon-Sat	0.044^{**}	2.248	0.143	2.643	−0.501	10.809
Tue-Mon^{+}	0.015	0.754	0.143	2.782	−0.504	11.145
Wed-Tue^{+}	0.035^{*}	1.748	0.144	2.723	−1.114	18.372
Thu-Wed^{+}	0.083^{***}	4.237	0.138	2.610	−0.618	11.362
Fri-Thu^{+}	0.085^{***}	4.337	0.138	2.551	−0.540	9.501
			Panel F: 1975–2024			
Mon-Fri	−0.022	−1.154	0.220	2.270	−0.887	10.298
Tue-Mon^{+}	-0.054^{**}	−2.759	0.222	2.437	−0.919	13.521
Wed-Tue^{+}	-0.035^{*}	−1.778	0.221	2.277	−1.341	15.273
Thu-Wed^{+}	−0.009	−0.435	0.219	2.257	−0.983	9.103
Fri-Thu^{+}	-0.046^{**}	−2.381	0.219	2.285	−1.275	15.054

Table 2: Decomposition of AR(1) Coefficients for Different Weekly Intervals

This table reports the components of the weekly AR(1) coefficient ρ for 1953–2024 and two subsamples. Weekly returns are constructed under five interval definitions: Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$. For the full sample (Part I), Panel A presents OLS coefficients from regressions of daily returns on future weekly returns; Panel B reports coefficients from regressions of weekly returns on future daily returns; Panel C reports daily-on-future-daily coefficients (lags 1–9). "+" and "++" denote the following week and the week after the following week, respectively. Parts II and III report the corresponding results for 1953–1988 and 1989–2024. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Part I: 1953–2024

Panel A: Daily Return Predicts Future Weekly Return

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue-Mon$^+$	−0.073**	−2.060								
Wed-Tue$^+$	−0.003	−0.090	0.057	1.520						
Thu-Wed$^+$	−0.003	−0.094	0.027	0.746	0.074**	1.991				
Fri-Thu$^+$	−0.029	−0.890	−0.027	−0.729	−0.037	−0.984	0.053	1.431		
Mon$^+$-Fri$^+$	0.006	0.197	−0.101***	−2.732	0.028	0.740	−0.001	−0.027	0.072*	1.788
Tue$^+$-Mon^{++}			−0.033	−0.825	0.061	1.476	−0.041	−1.016	−0.163***	−3.722
Wed$^+$-Tue^{++}					0.006	0.158	−0.033	−0.860	−0.093**	−2.255
Thu$^+$-Wed^{++}							0.023	0.617	−0.011	−0.263
Fri$^+$-Thu^{++}									−0.032	−0.791

Panel B: Weekly Return Predicts Future Daily Return

	Mon-Fri	t-stat.	Tue-Mon$^+$	t-stat.	Wed-Tue$^+$	t-stat.	Thu-Wed$^+$	t-stat.	Fri-Thu$^+$	t-stat.
Mon$^+$	0.075***	8.568								
Tue$^+$	−0.045***	−6.224	−0.054***	−8.027						
Wed$^+$	−0.019***	−2.696	−0.017**	−2.502	−0.013*	−1.857				
Thu$^+$	−0.013*	−1.744	−0.005	−0.742	0.005	0.659	0.027***	3.676		
Fri$^+$	0.005	0.675	−0.004	−0.603	0.010	1.490	−0.002	−0.316	0.008	1.244
Mon^{++}			0.040***	4.883	0.032***	3.647	0.027***	2.982	0.034***	3.851
Tue^{++}					−0.041***	−5.692	−0.032***	−4.389	−0.033***	−4.542
Wed^{++}							0.005	0.705	−0.005	−0.762
Thu^{++}									−0.017**	−2.272

Panel C: Daily Return Predicts Future Daily Return

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.092***	−6.492								
Wed	−0.029**	−2.002	0.007	0.443						
Thu	0.023	1.515	0.027	1.638	0.058***	3.448				
Fri	−0.026*	−1.944	0.044***	2.827	0.003	0.211	0.057***	3.634		
Mon$^+$	0.054***	3.029	0.008	0.411	0.029	1.445	0.110***	5.539	0.203***	9.374
Tue$^+$	−0.021	−1.478	−0.026	−1.552	−0.026	−1.515	−0.075***	−4.466	−0.093***	−5.202
Wed$^+$	−0.028*	−1.938	−0.023	−1.397	0.011	0.674	−0.019	−1.179	−0.037**	−2.073
Thu$^+$	−0.005	−0.321	−0.029*	−1.721	−0.057***	−3.340	−0.011	−0.670	0.041**	2.227
Fri$^+$	0.010	0.722	−0.033**	−2.112	0.070***	4.439	0.001	0.046	−0.030*	−1.766
Mon^{++}			0.080***	3.969	0.066***	3.223	0.069***	3.375	−0.050**	−2.232
Tue^{++}					−0.081***	−4.775	−0.066***	−3.983	−0.022	−1.222
Wed^{++}							0.036**	2.167	0.046**	2.570
Thu^{++}									0.018	1.007

Table 2–Continued

Part II: 1953–1988

Panel D: Daily Return Predicts Future Weekly Return										
	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue-Mon^{+}	0.141***	2.697								
Wed-Tue^{+}	0.084*	1.687	0.257***	4.012						
Thu-Wed^{+}	0.175***	3.804	0.092	1.539	0.280***	4.869				
Fri-Thu^{+}	0.094**	2.027	0.049	0.821	0.133**	2.281	0.250***	4.031		
Mon^{+}-Fri^{+}	0.067	1.472	0.059	0.988	0.144**	2.505	−0.053	−0.860	0.382***	5.954
Tue^{+}-Mon^{++}			−0.021	−0.306	0.097	1.494	−0.188***	−2.677	−0.063	−0.855
Wed^{+}-Tue^{++}					0.048	0.772	−0.099	−1.466	0.007	0.107
Thu^{+}-Wed^{++}							−0.044	−0.702	0.110*	1.694
Fri^{+}-Thu^{++}									0.074	1.135

Panel E: Weekly Return Predicts Future Daily Return										
	Mon-Fri	t-stat.	Tue-Mon^{+}	t-stat.	Wed-Tue^{+}	t-stat.	Thu-Wed^{+}	t-stat.	Fri-Thu^{+}	t-stat.
Mon^{+}	0.184***	16.124								
Tue^{+}	−0.034***	−3.771	−0.015*	−1.873						
Wed^{+}	−0.039***	−4.120	−0.050***	−5.925	−0.032***	−3.611				
Thu^{+}	−0.007	−0.774	0.011	1.402	0.018**	2.186	0.045***	5.162		
Fri^{+}	−0.008	−0.904	−0.001	−0.080	−0.002	−0.247	−0.004	−0.474	0.038***	4.509
Mon^{++}			0.067***	6.251	0.085***	7.587	0.106***	8.852	0.123***	10.428
Tue^{++}					−0.018**	−2.086	−0.013	−1.375	−0.024***	−2.715
Wed^{++}							−0.018*	−1.870	−0.025***	−2.635
Thu^{++}									−0.012	−1.318

Panel F: Daily Return Predicts Future Daily Return										
	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	0.024	1.321								
Wed	−0.118***	−6.190	0.179***	7.401						
Thu	0.054***	3.059	0.021	0.911	0.149***	6.888				
Fri	−0.001	−0.059	−0.009	−0.403	0.032	1.514	0.280***	12.803		
Mon^{+}	0.186***	7.654	0.094***	2.944	0.135***	4.449	0.236***	7.258	0.558***	17.377
Tue^{+}	−0.034*	−1.860	−0.011	−0.487	0.019	0.820	−0.090***	−3.673	−0.108***	−4.267
Wed^{+}	−0.022	−1.132	0.005	0.212	−0.045*	−1.910	−0.139***	−5.481	−0.061**	−2.292
Thu^{+}	−0.029*	−1.656	−0.024	−1.070	−0.002	−0.107	−0.023	−0.963	0.059**	2.363
Fri^{+}	−0.028	−1.632	0.001	0.026	0.043**	2.008	−0.028	−1.224	−0.032	−1.359
Mon^{++}			0.008	0.266	0.089***	2.904	0.094***	2.832	0.085**	2.440
Tue^{++}					−0.032	−1.390	0.000	0.020	−0.037	−1.458
Wed^{++}							−0.083***	−3.270	0.043	1.635
Thu^{++}									0.022	0.901

Table 2–Continued

Part III: 1989–2024

Panel G: Daily Return Predicts Future Weekly Return

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue-Mon^{+}	−0.215***	−4.421								
Wed-Tue^{+}	−0.060	−1.317	−0.032	−0.666						
Thu-Wed^{+}	−0.120***	−2.618	−0.001	−0.022	−0.032	−0.651				
Fri-Thu^{+}	−0.110**	−2.366	−0.060	−1.244	−0.126**	−2.481	−0.026	−0.531		
Mon^{+}-Fri^{+}	−0.033	−0.715	−0.172***	−3.545	−0.032	−0.635	0.020	0.407	−0.067	−1.260
Tue^{+}-Mon^{++}			−0.039	−0.748	0.041	0.769	0.018	0.346	−0.209***	−3.711
Wed^{+}-Tue^{++}					−0.016	−0.324	−0.007	−0.142	−0.137***	−2.645
Thu^{+}-Wed^{++}							0.049	1.032	−0.065	−1.242
Fri^{+}-Thu^{++}									−0.080	−1.502

Panel H: Weekly Return Predicts Future Daily Return

	Mon-Fri	t-stat.	Tue-Mon^{+}	t-stat.	Wed-Tue^{+}	t-stat.	Thu-Wed^{+}	t-stat.	Fri-Thu^{+}	t-stat.
Mon^{+}	0.001	0.076								
Tue^{+}	−0.052***	−4.773	−0.083***	−8.032						
Wed^{+}	−0.007	−0.640	0.008	0.761	0.002	0.155				
Thu^{+}	−0.017	−1.489	−0.017	−1.605	−0.006	−0.506	0.015	1.285		
Fri^{+}	0.013	1.257	−0.006	−0.635	0.020*	1.852	−0.001	−0.099	−0.011	−1.110
Mon^{++}			0.018	1.500	−0.013	−1.017	−0.030**	−2.344	−0.029**	−2.248
Tue^{++}					−0.059***	−5.278	−0.046***	−4.094	−0.038***	−3.503
Wed^{++}							0.021*	1.905	0.007	0.678
Thu^{++}									−0.020*	−1.788

Panel I: Daily Return Predicts Future Daily Return

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.170***	−8.032								
Wed	0.031	1.467	−0.066***	−2.979						
Thu	0.003	0.134	0.030	1.278	0.011	0.424				
Fri	−0.040*	−1.934	0.068***	3.114	−0.014	−0.605	−0.035	−1.609		
Mon^{+}	−0.044*	−1.702	−0.032	−1.208	−0.022	−0.791	0.061**	2.367	0.050*	1.724
Tue^{+}	−0.014	−0.643	−0.032	−1.386	−0.048*	−1.957	−0.068***	−2.929	−0.086***	−3.409
Wed^{+}	−0.029	−1.341	−0.034	−1.533	0.038	1.634	0.027	1.206	−0.029	−1.166
Thu^{+}	0.012	0.539	−0.030	−1.271	−0.086***	−3.456	−0.007	−0.294	0.031	1.192
Fri^{+}	0.039*	1.888	−0.047**	−2.152	0.083***	3.614	0.011	0.508	−0.032	−1.319
Mon^{++}			0.112***	4.196	0.059**	2.088	0.060**	2.252	−0.107***	−3.612
Tue^{++}					−0.105***	−4.322	−0.093***	−4.021	−0.014	−0.556
Wed^{++}							0.082***	3.697	0.044*	1.800
Thu^{++}									0.016	0.591

Table 3: Correlations of AR(1) Coefficients for Different Weekly Intervals

This table reports pairwise correlations of OLS-estimated AR(1) coefficients (ρ) for weekly log returns on the VW CRSP index over 1953–2024 across five weekly interval definitions: Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$. Each ρ is estimated using a ten-year rolling window updated annually, beginning with 1953–1962. Part I (Panels A–C) reports correlations of the levels of ρ for the full sample and the two subsamples. Part II (Panels D–F) reports correlations of changes in ρ ($\Delta\rho$), for the same periods.

	Tue-Mon$^+$	Wed-Tue$^+$	Thu-Wed$^+$	Fri-Thu$^+$	Tue-Mon$^+$	Wed-Tue$^+$	Thu-Wed$^+$	Fri-Thu$^+$	Tue-Mon$^+$	Wed-Tue$^+$	Thu-Wed$^+$	Fri-Thu$^+$
	Part I: Correlations of ρ for Different Intervals											
	Panel A: 1962–2024				Panel B: 1962–1993				Panel C: 1994–2024			
Mon-Fri	0.715	0.705	0.939	0.934	0.171	-0.069	0.928	0.969	0.537	0.260	0.615	0.576
Tue-Mon$^+$		0.749	0.775	0.688		-0.436	-0.018	0.075		0.648	0.839	0.487
Wed-Tue$^+$			0.809	0.619			0.134	-0.068			0.612	-0.140
Thu-Wed$^+$				0.909				0.950				0.373
	Part II: Correlations of $\Delta\rho$ for Different Intervals											
	Panel D: 1962–2024				Panel E: 1962–1993				Panel F: 1994–2024			
Mon-Fri	0.552	0.194	0.595	0.783	0.546	-0.122	0.732	0.837	0.589	0.383	0.568	0.754
Tue-Mon$^+$		0.635	0.582	0.529		0.358	0.431	0.179		0.747	0.614	0.647
Wed-Tue$^+$			0.508	0.222			0.237	-0.181			0.611	0.440
Thu-Wed$^+$				0.388				0.778				0.263

Table 4: Tuesday Following Nontrading Monday

This table reports regression coefficients linking weekly returns and Tuesday returns for the subsample of Tuesdays that follow nontrading Mondays, over 1953–2024 and two subsamples. In Panel A, we regress future weekly returns (for each of the five weekly interval definitions) on the Tuesday return. Panel B reports coefficients from regressions of the Tuesday return on lagged weekly returns. "+" and "++" denote the following week and the week after the following week, respectively; "−" and "−−" denote the prior week and two weeks prior, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Tuesday Return Predicts Future Weekly Return

	1953-2024	t-stat.	1953-1988	t-stat.	1989-2024	t-stat.
Wed-Tue$^+$	0.049	0.484	0.227	1.173	−0.003	−0.026
Thu-Wed$^+$	0.191*	1.952	0.257	1.356	0.176	1.503
Fri-Thu$^+$	0.279***	2.728	0.652***	3.261	0.161	1.344
Mon$^+$-Fri$^+$	0.170	1.527	0.713***	3.417	−0.008	−0.059
Tue$^+$-Mon^{++}	0.180	1.606	0.643***	3.104	0.026	0.192

Panel B: Weekly Return Predicts Future Tuesday Return

	1953-2024	t-stat.	1953-1988	t-stat.	1989-2024	t-stat.
Tue$^-$-Mon	0.063	1.595	0.025	0.466	0.080	1.456
Mon$^-$-Fri$^-$	0.010	0.287	0.000	−0.003	0.016	0.314
Fri^{--}-Thu$^-$	−0.045	−1.388	0.011	0.206	−0.061	−1.437
Thu^{--}-Wed$^-$	−0.045	−1.393	0.034	0.674	−0.069*	−1.647
Wed^{--}-Tue$^-$	−0.053*	−1.664	0.022	0.473	−0.082*	−1.930

Table 5: Range of Daily Autocorrelations

This table reports summary statistics and correlations for the "range" series of daily autocorrelation coefficients at lags 1–9 across the five weekdays, 1962–2024. Using ten-year rolling windows (1953–2024, updated annually), we estimate for each lag n the OLS regression $r_{t+n} = \mu_n + \rho_n r_t + \varepsilon_{t+n}$ separately by weekday. For each calendar year in 1962–2024, the range for lag n is defined as maximum−minimum of estimated ρ_n across the five weekdays. We report the mean, standard deviation, minimum, maximum, and the AR(1) coefficient of each range series; we also report the cross-lag correlations among the nine range series.

	1	2	3	4	5	6	7	8	9
Mean	0.394	0.324	0.231	0.206	0.234	0.210	0.168	0.179	0.178
St.Dev.	0.163	0.148	0.113	0.086	0.063	0.112	0.061	0.062	0.095
Min.	0.160	0.119	0.063	0.056	0.072	0.075	0.049	0.071	0.067
Max.	0.750	0.612	0.544	0.447	0.351	0.444	0.330	0.328	0.384
AR(1)	0.883	0.851	0.924	0.881	0.591	0.835	0.745	0.706	0.761

Correlations

	1	2	3	4	5	6	7	8	9
1	1	0.833	0.697	0.326	0.448	−0.186	−0.042	0.128	−0.212
2		1	0.666	0.303	0.591	−0.076	0.016	0.299	−0.011
3			1	0.590	0.344	−0.307	−0.091	−0.020	−0.074
4				1	−0.068	−0.176	−0.176	−0.177	0.099
5					1	0.191	−0.080	0.423	0.098
6						1	0.424	0.460	0.801
7							1	0.208	0.465
8								1	0.404
9									1

Table 6: Asymmetric Daily Autocorrelations

This table reports coefficients from sign-conditional daily autocorrelation regressions, relating daily returns to future daily returns. Panels A, C, and E report ρ^{-} estimated on the subsample with $r_t < 0$; Panels B, D, and F report ρ^{+}, estimated on the subsample with $r_t \geq 0$. "+" and "++" denote the following week and the week after the following week, respectively. Parts I–III correspond to the full period (1953–2024) and the two subsamples (1953–1988; 1989–2024). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Part I: 1953–2024

	Panel A: $\rho^{-}(r_t < 0)$									
	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.204***	−8.574								
Wed	−0.060**	−2.539	−0.007	−0.180						
Thu	0.065***	2.653	0.040	1.075	0.044	1.210				
Fri	−0.043**	−1.973	0.079**	2.344	−0.030	−0.839	−0.028	−0.935		
Mon^{+}	0.123***	4.136	0.077*	1.733	−0.003	−0.072	0.157***	3.675	0.217***	4.257
Tue^{+}	−0.097***	−4.128	−0.084**	−2.286	−0.164***	−4.581	−0.134***	−4.241	−0.206***	−5.206
Wed^{+}	0.009	0.382	0.068*	1.903	0.094***	2.659	0.129***	3.996	−0.024	−0.587
Thu^{+}	0.000	0.021	0.023	0.611	−0.081**	−2.239	−0.028	−0.818	0.001	0.016
Fri^{+}	0.002	0.088	0.046	1.310	0.085***	2.685	0.012	0.400	−0.055	−1.458
Mon^{++}			0.179***	3.972	0.175***	3.772	0.099**	2.265	−0.047	−0.890
Tue^{++}					−0.273***	−7.519	−0.216***	−6.891	−0.108***	−2.719
Wed^{++}							0.086***	2.593	0.028	0.712
Thu^{++}									−0.003	−0.075

	Panel B: $\rho^{+}(r_t \geq 0)$									
	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.027	−0.952								
Wed	0.002	0.062	−0.107***	−3.828						
Thu	0.008	0.252	0.078***	2.725	−0.021	−0.714				
Fri	−0.022	−0.744	0.064**	2.337	−0.015	−0.581	0.042	1.455		
Mon^{+}	−0.073**	−2.026	−0.031	−0.891	−0.026	−0.757	0.078**	2.415	0.071**	2.060
Tue^{+}	0.122***	3.964	0.032	1.104	0.095***	3.169	−0.025	−0.773	−0.034	−1.088
Wed^{+}	−0.088***	−2.909	−0.088***	−3.107	0.021	0.729	−0.130***	−4.321	−0.111***	−3.666
Thu^{+}	0.017	0.549	−0.055**	−1.963	−0.025	−0.836	−0.021	−0.690	0.058*	1.817
Fri^{+}	0.066**	2.211	−0.096***	−3.694	0.075**	2.539	−0.003	−0.116	−0.075**	−2.479
Mon^{++}			0.103***	3.018	−0.055	−1.636	0.044	1.305	−0.181***	−5.118
Tue^{++}					0.011	0.365	0.047	1.467	0.110***	3.511
Wed^{++}							0.054*	1.829	0.067**	2.177
Thu^{++}									0.077**	2.329

Table 6–Continued

Part II: 1953–1988

Panel C: $\rho^{-}(r_t < 0)$

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.053**	−1.998								
Wed	−0.285***	−10.451	0.185***	3.243						
Thu	0.066**	2.533	0.010	0.186	0.236***	4.331				
Fri	−0.018	−0.717	−0.001	−0.018	0.003	0.056	0.290***	5.953		
Mon^{+}	0.224***	5.884	0.323***	4.810	0.308***	3.653	0.357***	4.318	0.771***	9.018
Tue^{+}	−0.020	−0.742	0.033	0.611	−0.141**	−2.344	−0.087	−1.524	−0.152**	−2.509
Wed^{+}	−0.030	−1.059	0.021	0.387	−0.186***	−2.963	−0.240***	−3.951	−0.216***	−3.294
Thu^{+}	−0.071***	−2.716	−0.027	−0.500	−0.019	−0.320	0.041	0.751	0.043	0.694
Fri^{+}	−0.054**	−2.142	0.159***	3.023	0.109**	2.013	−0.043	−0.811	−0.153***	−2.624
Mon^{++}			0.234***	3.071	0.198**	2.159	0.181**	2.095	0.143	1.519
Tue^{++}					−0.073	−1.227	−0.080	−1.462	−0.154**	−2.493
Wed^{++}							−0.199***	−3.313	−0.076	−1.114
Thu^{++}									−0.130**	−2.215

Panel D: $\rho^{+}(r_t \geq 0)$

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	0.072	1.517								
Wed	0.237***	4.694	0.110**	2.426						
Thu	0.080*	1.678	0.125***	2.875	0.021	0.587				
Fri	−0.024	−0.531	0.031	0.716	0.051	1.510	0.293***	7.344		
Mon^{+}	0.192***	3.302	−0.046	−0.706	−0.070	−1.533	0.196***	3.927	0.426***	8.911
Tue^{+}	−0.048	−0.978	−0.040	−0.905	0.107***	2.902	−0.078*	−1.809	−0.134***	−3.056
Wed^{+}	0.054	1.044	0.095**	2.002	−0.006	−0.167	−0.069	−1.630	−0.015	−0.350
Thu^{+}	0.054	1.174	0.016	0.385	0.060*	1.679	−0.028	−0.659	0.025	0.598
Fri^{+}	0.080*	1.711	−0.098**	−2.446	0.029	0.824	−0.087**	−2.207	−0.034	−0.861
Mon^{++}			−0.116**	−2.050	0.030	0.679	0.019	0.406	−0.016	−0.305
Tue^{++}					−0.054	−1.398	−0.022	−0.490	−0.005	−0.114
Wed^{++}							0.011	0.264	0.099**	2.330
Thu^{++}									0.161***	3.793

Part III: 1989–2024

Panel E: $\rho^{-}(r_t < 0)$

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.329***	−8.299								
Wed	0.120***	3.188	−0.078	−1.581						
Thu	0.066	1.565	0.047	0.888	0.000	0.000				
Fri	−0.067*	−1.858	0.092*	1.935	−0.052	−1.094	−0.111***	−2.696		
Mon^{+}	0.046	1.002	0.010	0.160	−0.050	−0.897	0.144***	2.725	0.114*	1.740
Tue^{+}	−0.166***	−4.260	−0.125**	−2.441	−0.166***	−3.471	−0.153***	−3.721	−0.234***	−4.269
Wed^{+}	0.039	1.016	0.074	1.493	0.171***	3.711	0.218***	5.403	0.028	0.523
Thu^{+}	0.063	1.566	0.039	0.729	−0.102**	−2.067	−0.063	−1.349	−0.016	−0.276
Fri^{+}	0.046	1.295	−0.007	−0.142	0.064	1.531	0.019	0.469	−0.033	−0.636
Mon^{++}			0.176***	3.015	0.197***	3.466	0.103*	1.952	−0.070	−1.019
Tue^{++}					−0.329***	−6.716	−0.244***	−5.907	−0.079	−1.446
Wed^{++}							0.147***	3.444	0.057	1.092
Thu^{++}									0.042	0.761

Panel F: $\rho^{+}(r_t \geq 0)$

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
Tue	−0.046	−1.283								
Wed	−0.070*	−1.790	−0.153***	−4.106						
Thu	−0.006	−0.152	0.068*	1.687	−0.040	−0.863				
Fri	−0.006	−0.160	0.082**	2.196	−0.056	−1.387	−0.041	−0.968		
Mon^{+}	−0.172***	−3.591	−0.041	−0.936	0.002	0.035	0.004	0.090	−0.108**	−2.166
Tue^{+}	0.173***	4.231	0.058	1.462	0.086*	1.859	−0.010	−0.197	0.015	0.321
Wed^{+}	−0.128***	−3.289	−0.147***	−3.909	0.054	1.232	−0.159***	−3.620	−0.155***	−3.593
Thu^{+}	0.012	0.277	−0.079**	−1.975	−0.079*	−1.679	−0.023	−0.510	0.088*	1.808
Fri^{+}	0.069*	1.719	−0.084**	−2.343	0.115**	2.498	0.062	1.368	−0.079*	−1.744
Mon^{++}			0.156***	3.462	−0.142***	−2.777	0.023	0.470	−0.290***	−5.863
Tue^{++}					0.056	1.292	0.094**	2.003	0.176***	3.823
Wed^{++}							0.077*	1.815	0.068	1.496
Thu^{++}									0.045	0.892

Table 7: AR(1) Coefficients for Different Monthly Intervals

This table reports, for each monthly interval definition, OLS estimates of the AR(1) coefficient (ρ) and the corresponding t-statistic for monthly log returns on the VW CRSP index over 1926–2024 and subsamples. We also report mean (%), standard deviation (%), skewness, and kurtosis. The eleven interval definitions begin on calendar days 1, 4, ..., 28, and 31, and end on the day before the same day of the following month (e.g., May 10–June 9). When a start (end) day does not exist, the next (previous) available day is used as a substitute. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Interval	ρ	t-stat.	Mean	St.Dev.	Skew.	Kurt.
			Panel A: 1926–2024			
Mo1	0.088***	3.042	0.791	5.315	−0.564	9.711
Mo4	0.062**	2.129	0.791	5.392	−0.329	10.038
Mo7	0.016	0.541	0.791	5.466	−0.422	11.019
Mo10	0.013	0.457	0.791	5.491	−0.549	13.554
Mo13	0.024	0.838	0.792	5.439	−1.154	16.222
Mo16	0.038	1.312	0.793	5.178	−0.743	11.633
Mo19	0.045	1.553	0.792	5.294	−0.727	13.854
Mo22	0.058**	2.001	0.794	5.350	−1.016	11.016
Mo25	0.064**	2.213	0.793	5.397	−0.757	11.663
Mo28	0.063**	2.189	0.792	5.447	−0.768	11.062
Mo31	0.084***	2.908	0.791	5.324	−0.648	9.985
			Panel B: 1926–1974			
Mo1	0.115***	2.801	0.627	6.013	−0.362	10.013
Mo4	0.103**	2.498	0.632	6.004	−0.070	10.495
Mo7	0.032	0.768	0.634	6.124	−0.265	11.695
Mo10	0.052	1.260	0.634	6.129	−0.259	13.870
Mo13	0.049	1.176	0.639	6.074	−0.898	16.351
Mo16	0.055	1.325	0.641	5.742	−0.542	12.221
Mo19	0.065	1.574	0.639	5.918	−0.255	13.101
Mo22	0.090**	2.178	0.641	5.775	−0.477	9.284
Mo25	0.109***	2.645	0.644	5.927	−0.203	11.186
Mo28	0.119***	2.884	0.648	6.018	−0.091	8.991
Mo31	0.111***	2.693	0.647	6.038	−0.478	10.245
			Panel C: 1975–2024			
Mo1	0.043	1.050	0.952	4.527	−0.896	6.033
Mo4	−0.008	−0.203	0.946	4.716	−0.771	7.068
Mo7	−0.019	−0.466	0.945	4.732	−0.661	6.736
Mo10	−0.057	−1.396	0.944	4.784	−1.051	10.081
Mo13	−0.022	−0.535	0.941	4.736	−1.550	12.564
Mo16	0.003	0.079	0.941	4.558	−1.041	8.240
Mo19	0.006	0.138	0.943	4.600	−1.600	13.135
Mo22	0.007	0.165	0.944	4.897	−1.822	13.631
Mo25	−0.010	−0.250	0.939	4.822	−1.690	11.425
Mo28	−0.027	−0.652	0.933	4.823	−1.970	14.529
Mo31	0.030	0.743	0.932	4.516	−0.912	6.115

Table 8: Within-Month Timing of Weekly Interval and AR(1) Coefficients

This table reports, by within-month timing, OLS estimates of the weekly AR(1) coefficient (ρ) and the corresponding t-statistic for VW CRSP weekly log returns over 1953–2024 and the subperiods 1953–1988 and 1989–2024. Weekly intervals are Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$, where "$^+$" denotes the following calendar week. Each weekly interval is assigned to a within-month "quarter" based on the calendar day of its last trading day: Q1$\leq$ 7, Q2($8-15$), Q3($16-24$), Q4($\geq$ 25). In Part I, we condition on the location of r_t (fix the subsample with r_t in quarter q) and estimate ρ from r_{t+1} on r_t. In Part II, we condition on the location of r_{t+1} (fix the subsample with r_{t+1} in quarter q) and estimate ρ from r_{t+1} on r_t. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Part I: Within-Month Timing of r_t

	First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
Interval	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.
				Panel A: 1953–2024				
Mon-Fri	0.027	0.753	0.040	1.315	−0.014	−0.481	−0.066*	−1.879
Tue-Mon$^+$	−0.089**	−2.534	0.052	1.614	0.014	0.481	−0.202***	−5.847
Wed-Tue$^+$	−0.071**	−2.191	0.081**	2.318	0.013	0.472	−0.094**	−2.502
Thu-Wed$^+$	−0.022	−0.556	0.105***	3.464	0.019	0.670	−0.055	−1.539
Fri-Thu$^+$	0.001	0.016	0.041	1.379	−0.057**	−2.066	−0.063*	−1.718
				Panel B: 1953–1988				
Mon-Fri	0.032	0.633	0.087**	2.032	0.195***	4.549	0.013	0.265
Tue-Mon$^+$	−0.051	−0.990	0.132***	2.789	0.074*	1.868	−0.181***	−3.776
Wed-Tue$^+$	0.033	0.696	0.100*	1.876	0.096***	2.588	−0.073	−1.476
Thu-Wed$^+$	0.077	1.556	0.165***	3.686	0.218***	5.361	−0.062	−1.235
Fri-Thu$^+$	0.051	0.958	0.128***	2.961	0.166***	4.362	0.002	0.040
				Panel C: 1989–2024				
Mon-Fri	0.024	0.465	0.011	0.258	−0.147***	−3.675	−0.126**	−2.477
Tue-Mon$^+$	−0.116**	−2.389	−0.005	−0.111	−0.038	−0.871	−0.217***	−4.369
Wed-Tue$^+$	−0.139***	−3.142	0.067	1.441	−0.064	−1.582	−0.111**	−1.960
Thu-Wed$^+$	−0.105*	−1.776	0.075*	1.798	−0.116***	−3.018	−0.046	−0.920
Fri-Thu$^+$	−0.036	−0.648	−0.013	−0.320	−0.206***	−5.329	−0.100**	−2.008

Part II: Within-Month Timing of r_{t+1}

	First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
Interval	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.
				Panel D: 1953–2024				
Mon-Fri	−0.053	−1.550	0.006	0.183	0.062**	2.178	−0.042	−1.200
Tue-Mon$^+$	−0.162***	−4.948	−0.106***	−3.337	0.122***	3.920	−0.050	−1.445
Wed-Tue$^+$	−0.085**	−2.317	−0.078**	−2.555	0.101***	3.161	−0.005	−0.161
Thu-Wed$^+$	−0.070**	−2.054	0.014	0.394	0.083***	2.815	0.031	0.965
Fri-Thu$^+$	−0.068*	−1.958	−0.011	−0.318	0.051*	1.845	−0.072**	−2.205
				Panel E: 1953–1988				
Mon-Fri	−0.005	−0.119	0.043	0.908	0.131***	3.221	0.209***	4.090
Tue-Mon$^+$	−0.154***	−3.387	−0.046	−0.985	0.133***	2.869	0.087**	1.964
Wed-Tue$^+$	−0.073	−1.500	0.028	0.617	0.109**	2.265	0.099**	2.379
Thu-Wed$^+$	−0.084*	−1.732	0.083*	1.825	0.168***	3.934	0.266***	5.741
Fri-Thu$^+$	0.003	0.059	0.053	1.081	0.141***	3.507	0.170***	3.804
				Panel F: 1989–2024				
Mon-Fri	−0.089*	−1.787	−0.017	−0.354	0.020	0.498	−0.199***	−4.279
Tue-Mon$^+$	−0.167***	−3.555	−0.146***	−3.333	0.116***	2.760	−0.193***	−3.735
Wed-Tue$^+$	−0.094*	−1.735	−0.149***	−3.603	0.095**	2.216	−0.121**	−2.565
Thu-Wed$^+$	−0.057	−1.182	−0.038	−0.745	0.033	0.821	−0.131***	−2.999
Fri-Thu$^+$	−0.111**	−2.312	−0.059	−1.121	−0.005	−0.128	−0.239***	−5.301

Table 9: AR(1) Coefficients for Different Weekly Intervals of International Markets

This table reports, for each weekly interval, OLS estimates of the AR(1) coefficient (ρ) and the corresponding t-statistic for weekly log returns in eight international stock markets over 1989–2024. We also report weekly skewness and kurtosis. The five interval definitions are Mon-Fri, Tue-Mon$^+$, Wed-Tue$^+$, Thu-Wed$^+$, and Fri-Thu$^+$, where "+" denotes the following calendar week. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Australia		Denmark		Hong Kong		Japan		Singapore		Sweden		Switzerland		UK	
	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.	ρ	t-stat.
Mon-Fri	0.019	0.829	−0.017	−0.746	0.031	1.341	−0.016	−0.692	0.031	1.361	0.002	0.101	−0.025	−1.067	−0.031	−1.363
Tue-Mon$^+$	−0.040*	−1.714	−0.029	−1.255	−0.107***	−4.651	−0.081***	−3.499	−0.049**	−2.128	−0.017	−0.753	−0.082***	−3.574	−0.043*	−1.872
Wed-Tue$^+$	−0.050**	−2.161	−0.026	−1.124	−0.040*	−1.732	−0.039*	−1.673	0.019	0.821	−0.029	−1.241	−0.036	−1.569	−0.037	−1.607
Thu-Wed$^+$	0.013	0.541	−0.014	−0.599	0.008	0.350	−0.036	−1.548	0.060***	2.627	−0.039*	−1.673	−0.033	−1.415	−0.040*	−1.720
Fri-Thu$^+$	0.009	0.409	−0.020	−0.876	−0.003	−0.139	−0.040*	−1.751	0.041*	1.770	−0.040*	−1.734	−0.002	−0.102	−0.028	−1.211
	Skew.	Kurt.	Skew.	Kurt.	Skew.	Kurt.	Skew.	Kurt.	Skew.	Kurt.	Skew.	Kurt .	Skew.	Kurt.	Skew.	Kurt.
Mon-Fri	−1.108	10.638	−1.177	10.385	−0.524	7.077	−0.553	7.483	−0.610	10.035	−0.580	7.993	−1.297	14.961	−1.085	14.290
Tue-Mon$^+$	−0.663	7.809	−0.917	8.616	−0.775	12.457	−0.647	7.886	−0.620	12.043	−0.359	6.120	−0.928	8.519	−0.571	8.023
Wed-Tue$^+$	−0.812	8.946	−0.564	9.561	−0.736	10.808	−0.556	7.814	−0.567	9.129	−0.382	6.933	−0.873	8.401	−0.485	8.165
Thu-Wed$^+$	−0.709	7.515	−0.761	7.052	−0.675	6.754	−0.409	6.690	−0.489	8.229	−0.469	6.803	−0.774	8.000	−0.545	8.540
Fri-Thu$^+$	−1.041	9.952	−0.859	8.051	−0.858	8.550	−0.440	5.851	−0.518	8.599	−0.596	8.132	−1.066	9.943	−1.001	12.212

Table 10: Daily Autocorrelations of International Markets

This table reports correlation coefficients between daily returns and future daily returns for eight international stock markets over 1989–2024. "+" and "++" denote the following week and the week after the following week, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Mon	*t*-stat.	Tue	*t*-stat.	Wed	*t*-stat.	Thu	*t*-stat.	Fri	*t*-stat.
Panel A: Australia										
Tue	−0.090***	−4.379								
Wed	−0.016	−0.744	−0.062***	−2.626						
Thu	0.011	0.506	−0.006	−0.248	0.087***	3.654				
Fri	−0.049**	−2.289	−0.068***	−2.904	0.012	0.524	0.018	0.744		
Mon^{+}	0.056**	2.228	0.001	0.028	0.102***	3.643	0.136***	4.918	−0.030	−1.068
Tue^{+}	−0.070***	−3.314	−0.010	−0.421	−0.029	−1.236	−0.047**	−2.004	−0.048**	−2.017
Wed^{+}	−0.019	−0.879	0.036	1.551	−0.032	−1.370	−0.032	−1.374	−0.024	−1.015
Thu^{+}	0.026	1.238	−0.044*	−1.839	−0.032	−1.327	0.031	1.298	0.045**	1.854
Fri^{+}	0.087***	4.062	−0.008	−0.322	−0.014	−0.593	−0.008	−0.330	0.010	0.398
Mon^{++}			0.001	0.034	0.042	1.508	0.068**	2.441	−0.012	−0.411
Tue^{++}					−0.014	−0.593	−0.033	−1.411	−0.031	−1.308
Wed^{++}							−0.046**	−1.990	0.045*	1.885
Thu^{++}									0.076***	3.136
Panel B: Denmark										
Tue	0.017	0.819								
Wed	−0.023	−1.093	0.022	0.902						
Thu	−0.059***	−2.681	0.048*	1.957	0.080***	3.370				
Fri	0.019	0.857	0.030	1.229	−0.032	−1.317	0.082***	3.451		
Mon^{+}	−0.056**	−2.253	0.039	1.432	0.007	0.275	0.011	0.400	0.098***	3.665
Tue^{+}	−0.054**	−2.547	−0.020	−0.845	0.038*	1.647	0.003	0.109	−0.039	−1.598
Wed^{+}	0.009	0.415	−0.060**	−2.502	0.004	0.156	0.002	0.093	−0.051**	−2.039
Thu^{+}	−0.001	−0.057	−0.006	−0.229	0.007	0.275	−0.023	−0.943	0.043*	1.649
Fri^{+}	−0.023	−1.018	−0.011	−0.442	−0.012	−0.516	−0.002	−0.076	−0.009	−0.343
Mon^{++}			0.027	0.994	0.024	0.892	0.062**	2.309	−0.032	−1.160
Tue^{++}					0.028	1.212	−0.013	−0.534	−0.088***	−3.544
Wed^{++}							0.027	1.151	−0.009	−0.375
Thu^{++}									0.019	0.754
Panel C: Hong Kong										
Tue	−0.092***	−5.177								
Wed	−0.091***	−4.524	−0.010	−0.368						
Thu	−0.015	−0.754	0.075***	2.927	0.078***	3.405				
Fri	−0.027	−1.427	−0.042	−1.747	0.011	0.509	0.027	1.157		
Mon^{+}	−0.078***	−2.994	0.076**	2.324	0.159***	5.437	0.084***	2.652	0.217***	6.696
Tue^{+}	0.006	0.327	−0.015	−0.651	−0.027	−1.232	0.022	0.925	−0.154***	−6.387
Wed^{+}	0.012	0.574	−0.088***	−3.315	−0.090***	−3.764	−0.053**	−2.053	0.070***	2.595
Thu^{+}	0.048**	2.522	−0.039	−1.544	0.003	0.129	0.027	1.119	0.034	1.332
Fri^{+}	−0.015	−0.804	0.034	1.383	−0.010	−0.448	−0.040*	−1.686	0.022	0.880
Mon^{++}			−0.031	−0.937	0.007	0.235	0.066**	2.061	−0.013	−0.401
Tue^{++}					0.032	1.430	−0.010	−0.420	−0.036	−1.462
Wed^{++}							0.019	0.729	−0.013	−0.473
Thu^{++}									0.014	0.543
Panel D: Japan										
Tue	−0.065***	−3.215								
Wed	−0.100***	−4.666	0.053**	2.293						
Thu	−0.043**	−2.047	−0.003	−0.130	0.006	0.257				
Fri	−0.008	−0.381	−0.046**	−1.969	0.067***	2.840	0.072***	3.122		
Mon^{+}	−0.038	−1.395	0.034	1.142	0.058*	1.908	0.049*	1.663	0.198***	6.745
Tue^{+}	−0.058***	−2.679	0.001	0.022	−0.079***	−3.206	−0.051**	−2.062	−0.100***	−3.971
Wed^{+}	−0.018	−0.860	−0.043*	−1.809	−0.041*	−1.705	0.013	0.532	−0.037	−1.509
Thu^{+}	0.028	1.287	−0.057**	−2.384	−0.063***	−2.596	0.053**	2.200	0.027	1.101
Fri^{+}	0.028	1.311	−0.013	−0.580	0.006	0.255	0.053**	2.225	0.005	0.196
Mon^{++}			−0.016	−0.555	0.080***	2.704	0.094***	3.192	−0.028	−0.919
Tue^{++}					−0.012	−0.498	−0.049**	−2.000	−0.047*	−1.901
Wed^{++}							−0.017	−0.709	−0.023	−0.925
Thu^{++}									0.038	1.538

Table 10–Continued

	Mon	t-stat.	Tue	t-stat.	Wed	t-stat.	Thu	t-stat.	Fri	t-stat.
					Panel E: Singapore					
Tue	−0.049***	−2.752								
Wed	−0.043**	−2.285	0.073***	2.948						
Thu	−0.010	−0.512	0.106***	4.122	0.141***	5.884				
Fri	0.025	1.328	−0.034	−1.386	0.092***	3.944	0.138***	6.083		
Mon^{+}	0.029	1.203	0.071**	2.261	0.088***	2.978	0.139***	4.779	0.242***	7.704
Tue^{+}	−0.014	−0.786	−0.047**	−1.977	−0.014	−0.638	−0.030	−1.320	−0.084***	−3.541
Wed^{+}	0.002	0.120	−0.069***	−2.750	−0.013	−0.563	−0.047**	−1.983	0.059**	2.401
Thu^{+}	0.010	0.497	−0.065**	−2.540	−0.031	−1.268	−0.010	−0.420	−0.027	−1.071
Fri^{+}	−0.028	−1.490	−0.026	−1.041	0.031	1.356	0.040*	1.731	0.018	0.739
Mon^{++}			0.032	0.996	−0.010	−0.335	0.029	0.983	−0.057*	−1.820
Tue^{++}					0.025	1.120	−0.003	−0.130	−0.009	−0.380
Wed^{++}							0.033	1.399	−0.007	−0.284
Thu^{++}									0.049*	1.939
					Panel F: Sweden					
Tue	−0.010	−0.494								
Wed	−0.015	−0.735	−0.021	−0.866						
Thu	−0.041*	−1.859	0.004	0.145	0.043*	1.738				
Fri	−0.008	−0.395	0.027	1.128	−0.005	−0.222	0.030	1.360		
Mon^{+}	−0.070***	−2.876	0.000	−0.009	−0.028	−1.043	0.025	0.947	0.146***	5.177
Tue^{+}	−0.044**	−2.145	−0.033	−1.408	−0.017	−0.733	−0.050**	−2.223	−0.095***	−3.901
Wed^{+}	−0.005	−0.245	−0.041*	−1.701	0.028	1.203	0.017	0.725	0.037	1.461
Thu^{+}	0.023	1.042	0.026	1.042	−0.031	−1.239	−0.012	−0.508	0.072***	2.723
Fri^{+}	−0.008	−0.379	0.031	1.320	0.039	1.695	0.010	0.455	0.048*	1.939
Mon^{++}			0.060**	2.147	−0.013	−0.489	0.050*	1.876	−0.030	−1.020
Tue^{++}					0.001	0.061	−0.024	−1.069	−0.084***	−3.430
Wed^{++}							0.014	0.625	−0.012	−0.488
Thu^{++}									0.062**	2.340
					Panel G: Switzerland					
Tue	−0.049**	−2.478								
Wed	−0.036*	−1.893	0.017	0.758						
Thu	−0.089***	−4.051	0.034	1.333	0.089***	3.323				
Fri	0.031	1.548	0.024	1.015	−0.010	−0.422	0.142***	6.696		
Mon^{+}	−0.080***	−3.231	0.043	1.473	0.023	0.772	0.018	0.667	0.085***	2.953
Tue^{+}	−0.002	−0.116	−0.057**	−2.409	0.001	0.036	−0.054**	−2.432	−0.114***	−4.738
Wed^{+}	−0.007	−0.340	−0.026	−1.166	0.001	0.025	0.034	1.624	0.011	0.475
Thu^{+}	0.036*	1.657	−0.023	−0.903	−0.010	−0.361	0.016	0.666	0.045*	1.715
Fri^{+}	0.024	1.168	0.036	1.504	−0.029	−1.167	−0.041*	−1.870	−0.058**	−2.399
Mon^{++}			−0.031	−1.070	0.059*	1.925	0.063**	2.352	−0.051*	−1.727
Tue^{++}					0.042*	1.692	−0.051***	−2.336	−0.054**	−2.258
Wed^{++}							0.019	0.905	0.018	0.803
Thu^{++}									0.014	0.531
					Panel H: UK					
Tue	−0.073***	−3.536								
Wed	−0.029	−1.392	−0.012	−0.499						
Thu	−0.065***	−2.892	0.016	0.633	0.054**	2.223				
Fri	0.038*	1.713	−0.013	−0.530	−0.007	−0.306	0.050**	2.198		
Mon^{+}	−0.037	−1.445	0.032	1.111	−0.082***	−2.907	0.012	0.465	0.045*	1.654
Tue^{+}	−0.041*	−1.909	−0.040**	−1.721	0.052**	2.235	−0.060***	−2.678	−0.097***	−4.237
Wed^{+}	0.024	1.106	−0.062***	−2.668	0.011	0.462	0.030	1.363	0.003	0.110
Thu^{+}	0.032	1.402	0.018	0.752	−0.041**	−1.678	0.008	0.348	0.036	1.509
Fri^{+}	−0.013	−0.600	0.030	1.225	0.033	1.375	0.025	1.063	−0.077***	−3.224
Mon^{++}			0.040	1.435	0.065**	2.298	0.066**	2.442	−0.071**	−2.522
Tue^{++}					−0.008	−0.356	−0.061***	−2.730	−0.026	−1.130
Wed^{++}							−0.004	−0.163	0.035	1.506
Thu^{++}									0.058**	2.383