Calendar Effects of Asset Pricing Factors[1]

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ABSTRACT

The literature finds that U.S. equity returns are higher overnight, on Fridays, in January, around the turn-of-the-month, and during macro announcements (e.g., FOMC, GDP, NFP, and ISM releases). We replicate 153 long–short factors and find that their premia are lower in all of these periods. On average, a factor loses 2.01 bps overnight but earns 5.45 bps intraday ($t = 8.54$); earns 5.77 bps on Mondays, 3.44 bps on midweek days, and 1.24 bps on Fridays (midweek−Monday difference: $t = -7.06$; Friday−midweek difference: $t = -5.34$); earns 0.22 bps in January but 3.71 bps on non-January days ($t = 3.66$); earns 1.89 bps during turn-of-the-month days versus 3.61 bps on other days ($t = 6.01$); earns 2.99 bps during three-day windows surrounding major macroeconomic announcements, compared with 3.71 bps on other days ($t = 4.62$). The results are robust in-sample and out-of-sample. Our results are consistent with sentiment-driven mispricing, as we find that the calendar effects of factors are stronger when news sentiment is high.

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Economists have discovered the calendar effect of the U.S. equity premium at various horizons. Stocks yield higher returns during overnight sessions and lower during intraday sessions (e.g., Boyarchenko, Larsen, and Whelan (2023), Bondarenko and Muravyev (2023), Lou, Polk, and Skouras (2019)), higher on Friday and lower on Mondays (e.g., Cross (1973), French (1980)), higher in January and lower in the remaining 11 months (e.g., Rozeff and Kinney (1976), Thaler (1987)), higher returns around the turn of the month (e.g., Lakonishok and Smidt (1988), Ariel (1987), McConnell and Xu (2008)), and higher during macroeconomic announcement windows (FOMC, GDP, NFP, ISM) (e.g., Lucca and Moench (2015)).

We find exactly the reverse of calendar effects on factor portfolios. We replicate 153 asset pricing factors and find that on average, their returns are lower during overnights, Fridays, Januaries, turn-of-the-months, and macro announcements. On average, a factor loses 2.01 bps overnight but earns 5.45 bps intraday ($t = 8.54$). Across the week, factors earn 5.77 bps on Mondays and 3.44 bps on midweek days, compared with only 1.24 bps on Fridays (midweek−Monday difference: $t = -7.06$; Friday−midweek difference: $t = -5.34$). At the monthly horizon, factors earn 0.22 bps in January versus 3.71 bps in other months ($t = 3.66$). Similarly, factor returns average 1.89 bps during turn-of-the-month days compared with 3.61 bps on other days ($t = 6.01$). Finally, factors earn 2.99 bps during three-day windows surrounding major macroeconomic announcements, compared with 3.71 bps on other days ($t = 4.62$). Both the long and short legs of factor portfolios contribute to these patterns. Table I summarizes our main findings.

It is of considerable interest to further study the underlying drivers of the reversed calendar effects in factor returns. In this paper, we consider two potential explanations for these findings: data mining and mispricing. First, the apparent return predictability could reflect data mining. As Fama (1998) argues, academics have tested thousands of potential predictors of returns, and it would therefore not be surprising to observe some variables predicting returns in-sample purely by chance, even if no true predictability exists. Second, the reversed calendar effects may reflect mispricing, as emphasized in behavioral models of

Table I
Average Daily Returns (bps) of Factors and U.S. Equity Premium

This table summarizes and compares the calendar effects between factor portfolios and U.S. equity premium. We report calendar effects by comparing the average daily returns across calendar events (non-events) that we study. We create our factor portfolio by equally aggregating the 153 factors studied by Jensen, Kelly, and Pedersen (2023). The upper panel shows the results for the equal-weighted aggregate factor portfolio. And the lower panel shows those for U.S. equity premium. The Macro Window column aggregates the 3-day windows of FOMC, GDP, NFP, and ISM announcements. Average daily returns are in basis points. Two-sample t-tests are conducted within each calendar group. t-statistics are in parentheses. We use CRSP U.S. daily stock return data from June 1992 to December 2024. *, **, *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

	Overnight	Intraday	Friday	Mid-Week	Monday	Jan	Non-Jan	Turn-of-Month	Non-TOM	Macro Window	Non-Macro
153 Factors Average	−2.01	5.45	1.24	3.44	5.77	0.22	3.71	1.89	3.61	2.99	3.71
Difference	−7.46***		−2.20***			−3.49***		−1.72***		−0.72***	
	(−8.54)		(−5.34)			(−3.66)		(−6.01)		(−4.62)	
				−2.33***							
				(−7.06)							
U.S. Equity	0.39	−5.52	3.96	−4.89	−15.61	5.08	−6.02	6.87	−6.45	−0.34	−8.09
Difference	5.91***		8.85***			11.10***		13.33***		7.75***	
	(5.93)		(3.32)			(2.85)		(3.74)		(3.19)	
				10.72***							
				(3.19)							

Note: For the day-of-the-week horizon, the first difference row is Friday vs. mid-week and the second is mid-week vs. Monday.

asset pricing (e.g., Barberis and Thaler (2003)).

A. Data Mining

It is possible that the observed calendar patterns arise from data mining. Researchers have tested a very large number of return predictors, and some may appear significant purely by chance. If certain calendar windows happen to exhibit unusual return realizations in the sample period, predictors that inadvertently load on stocks performing well or poorly during those windows may be selected as factors. In this case, the calendar patterns we observe would reflect the selection process of factors rather than a genuine economic mechanism.

To address the data-mining explanation, we compute factor returns using strictly out-of-sample data for each factor. The reversed calendar effects become weaker in the out-of-sample period but remain economically large and statistically significant, suggesting that they cannot be fully explained by data mining; Section III.A presents this evidence.

B. Sentiment-driven Mispricing

Behavioral models suggest that investor sentiment and attention fluctuate over time and may be systematically linked to calendar events such as month-ends, macroeconomic announcements, or periods of heightened market activity. During such periods, sentiment-driven demand for certain stocks may temporarily distort prices, generating predictable patterns in factor returns across calendar windows.

To better understand the mechanism, we incorporate a daily news-based sentiment index into our regressions to examine whether investor sentiment helps explain these patterns. We find that sentiment strongly conditions the calendar patterns: when sentiment is elevated, the erosion of factor predictability during Fridays, Januaries, turn-of-the-month periods, and macro announcement windows becomes significantly stronger. This points to a behavioral interpretation in which the calendar windows coincide with heightened investor attention and sentiment, increasing demand for popular or speculative stocks and compressing the return spread captured by factor strategies; Section III.B develops this evidence.

C. Motivation and Related Literature

Our paper relates to two strands of literature. The first documents calendar effects in the U.S. equity premium across a variety of horizons. For example, Boyarchenko, Larsen, and Whelan (2023) and Bondarenko and Muravyev (2023) show that stock returns are higher during overnight trading sessions and lower during intraday sessions. At the day-of-the-week horizon, Cross (1973) and French (1980) document that stock returns tend to be higher on Fridays and lower on Mondays. At the monthly horizon, Rozeff and Kinney (1976) and Thaler (1987) show that returns are significantly higher in January relative to the other months of the year. In addition, Lakonishok and Smidt (1988), Ariel (1987), and McConnell and Xu (2008) document elevated returns around the turn of the month, while Lucca and Moench (2015) find unusually high returns prior to FOMC announcements.

It is worth noting that the literature discussed above either primarily documents the existence of calendar patterns or explains them through rational, risk-based mechanisms. For example, Boyarchenko, Larsen, and Whelan (2023) interpret overnight return patterns through an inventory-risk channel, Bondarenko and Muravyev (2023) argue that returns around the European open reflect investors processing overnight information and resolving uncertainty, and Lucca and Moench (2015) conclude that the pre-FOMC drift is best viewed as an expected-return phenomenon that is not well explained by standard off-the-shelf theories. By contrast, our paper uncovers reversed calendar effects in factor portfolios and presents evidence more consistent with sentiment-driven mispricing, as the calendar effects of factors become stronger when news sentiment is high.

While the aforementioned studies document systematic calendar patterns in aggregate market returns, the calendar effects of factor portfolios are largely underexplored. Relatedly, Lou, Polk, and Skouras (2019) explore 14 factors and document that different investor clienteles trade at different times of the day, creating a "tug-of-war" between overnight and intraday returns that leads to predictable patterns in the timing of returns. Birru (2018), examining 19 factors, further demonstrates that day-of-the-week effects extend to the cross-section of returns, with factor returns varying systematically across weekdays. We contribute to the literature by documenting the calendar effects of factors in the aggregate.

Our paper also relates to the growing literature on large-scale studies of financial factors. Recent "mega studies," such as Harvey, Liu, and Zhu (2016), Hou, Xue, and Zhang (2020), and Kelly, Jensen, and Pedersen (2023), compile large and standardized sets of return predictors and provide a comprehensive assessment of factor profitability. Building on this literature, several recent papers study when factor returns are realized. For example, Engelberg, McLean, and Pontiff (2018) show that factor returns are approximately six times larger on earnings announcement days (see also Savor and Wilson (2016)), and Bowles, Reed, Ringgenberg, and Thornock (2024) document that factor returns are concentrated in the first month following information release dates.

The availability of large cross-sections of factors therefore provides a natural opportunity to examine whether factor returns vary systematically across calendar events. In contrast to the existing literature, which primarily studies calendar effects in the aggregate market or around firm-specific information events, we examine whether factor portfolios exhibit systematic calendar patterns. We show that they do—but strikingly, the patterns are the reverse of those observed in the U.S. equity premium.

The remainder of the paper is organized as follows. Section I describes the data. Section II documents stylized facts on factor returns across calendar events. Section III discusses potential explanations for the reversed calendar effects. Section IV concludes.

I. Sample and Data

We obtain daily stock return data from the Center for Research in Security Prices (CRSP US Daily) database, and we include delisting returns from CRSP following Shumway (1997). Our sample period is from June 1992 to December 2024. We start our sample from June 1992 because the open/close prices have been widely available since then.

We calculate the three types of returns in logarithms: close-to-close return, intraday return, and overnight return. We directly use the variable RET from CRSP to calculate the close-to-close return, as RET is the canonical daily return measure including dividends and splits, adjusted for all corporate actions. We define the three types of returns as follows:

$$\text{Close-to-close return} = \log(RET_t + 1)$$
$$\text{Intraday return} = \log\left(\frac{close_t}{open_t}\right)$$
$$\text{Overnight return} = \log\left(\frac{open_t}{close_t} \times (RET_t + 1)\right)$$

The definition implicitly assumes that all dividends, splits, and other corporate actions occur overnight rather than during trading hours. Equivalently, the overnight return equals the close-to-close return minus the intraday return.

We create our 153 cross-sectional factors following Jensen, Kelly, and Pedersen (2023); the underlying characteristics originate from research published in finance, economics, and accounting journals and are derived from CRSP and Compustat. Stocks are sorted each month on each of the factor characteristics. Extreme terciles are defined as the long and short sides of each factor strategy. Within each side, stocks are equally weighted. Our factor portfolios are rebalanced each month. Within a single factor portfolio, a stock is either held long (positive weight) or sold short (negative weight) each month. To study the joint behavior of factor portfolios, we aggregate the weights of the 153 monthly long-side (*Long*) and short-side (*Short*) factor portfolios, and the sum of all stock weights is defined as *Net*. That is, $Net = Long - Short$.

We study how factor portfolios behave during Mondays, Fridays, January trading days, and turn-of-the-month (TOM) periods. We also collect information on four major U.S. macro releases. The Federal Open Market Committee (FOMC) announcement dates are obtained from the Board of Governors of the Federal Reserve System. GDP release dates are taken from ALFRED (Federal Reserve Bank of St. Louis), which records the historical announcement dates of the Bureau of Economic Analysis (BEA) GDP reports. Nonfarm Payroll (NFP) announcement dates are obtained from the U.S. Bureau of Labor Statistics as part of the Employment Situation report. Because the Institute for Supply Management (ISM) does not provide a downloadable historical series of Manufacturing PMI release dates, we construct the ISM announcement dates following the release rule described by the Institute. For each of the four types of macroeconomic events, we also consider a three-day event window $[t-1, t+1]$ centered on the announcement date t.[2]

For comparison, we also study how factor portfolios behave during periods of heightened market uncertainty. Specifically, we examine volatile months, defined following the volatility-managed portfolio framework of Muir (2017), lagged volatile months, and NBER-defined recession months.

[2] Window days falling on non-trading days are dropped. For example, because NFP is released on Fridays, its three-day window typically contains two trading days.

To proxy for investor sentiment, we use the Daily News Sentiment Index (DNSI) provided by the Federal Reserve Bank of San Francisco, constructed using textual analysis of a large number of U.S. newspaper articles. The DNSI provides a high-frequency, real-time measure of daily news sentiment.

Table II provides descriptive statistics of the variables that we use in this paper. Panel A reports macroeconomic announcement and calendar event statistics. Panel B reports descriptive statistics for stock variables and news sentiment. The mean value for *Net* is -1.06×10^{-6}, the 99th percentile value is 2.36×10^{-4}, and the 1st percentile value is -2.23×10^{-4}. The positive overnight return average (0.3 bp), compared with the negative average of close-to-close returns (-6.3 bp) and intraday returns (-6.6 bp), suggests a modest overnight premium.

Table II
Summary Statistics

This table provides summary statistics for the calendar events (Panel A) and stock variables (Panel B) used in this study. We use FOMC, GDP, NFP, and ISM announcement dates and their three-day event window. Additionally, we construct five calendar-based indicators (i.e., volatile months and their lag, NBER recession months, and the last three trading days of months and quarters). We use the 153 cross-sectional factors studied in Jensen, Kelly, and Pedersen (2023). Stocks are sorted each month on each of the factor characteristics. Extreme terciles are defined as the long and short sides of each factor strategy. Aggregating the 153 factor portfolios, the sum of all stock weights is defined as *Net*. We use the three types of returns in logarithms: close-to-close return, intraday return, and overnight return. We use DNSI as a proxy for investor sentiment.

Panel A: Number of Observations Marked by the Events

	Count	Percent		Count	Percent
FOMC Date	1,596,879	3.8%	Volatile Month	9,002,462	21.5%
3-day FOMC Window	4,616,528	11.0%	Lagged Volatile Month	8,951,461	21.4%
GDP Announcement Date	2,235,350	5.3%	Quarter Last 3-day	1,445,765	3.5%
3-day GDP Window	5,793,688	13.8%	Month Last 3-day	4,139,039	9.9%
NFP Date	1,942,811	4.6%	Recession Month	2,899,950	6.9%
3-day NFP Window	3,925,207	9.4%			
ISM Date	1,935,020	4.6%			
3-day ISM Window	4,667,285	11.2%			
Total Observations	41,856,826	CRSP US Stock Daily Return, June 1992 – December 2024			

Panel B: Descriptive Summary for Stock Variables

Variable	Mean	Std. Dev.	1st%ile	5th%ile	25th%ile	Median	75th%ile	95th%ile	99th%ile
Net	−1.06E-06	9.75E-05	−2.23E-04	−1.57E-04	−6.72E-05	−2.38E-06	6.20E-05	1.64E-04	2.36E-04
Close-to-Close Return (bps)	−6.3	484.8	−1,335.3	−625.2	−159.1	0.0	144.7	606.2	1,347.3
Intraday Return (bps)	−6.6	430.7	−1,243.8	−588.4	−141.7	0.0	128.3	560.9	1,228.7
Overnight Return (bps)	0.3	340.7	−953.1	−365.1	−61.9	0.0	66.0	363.8	923.7
News Sentiment	0.05	0.19	−0.45	−0.30	−0.06	0.08	0.19	0.31	0.38

II. Factor Returns across Calendar Events

Engelberg, McLean, and Pontiff (2018) find that factors' predictive power is stronger on news announcement days. We closely follow their methodology to formally test the return predictability of factors during specific periods. Specifically, we sum the weights of 153 monthly long-side (*Long*) and short-side (*Short*) factor portfolios, and define:

$$Net = Long - Short$$

Then, we study how the synthetic factor portfolio behaves on macro announcement dates, individual weekdays, the last three trading days of the month, and January trading days, through the following regression set forth in Engelberg et al. (2018):

$$\begin{aligned} ret_{i,t} = {} & \alpha_i + \beta_1 Net_{i,t} + \beta_2 Net_{i,t} \times event_t + \beta_3 event_t \\ & + \sum_{j=1}^{10} \gamma_j ret_{i,t-j} + \sum_{j=1}^{10} \delta_j ret^2_{i,t-j} + \sum_{j=1}^{10} \rho_j volume_{i,t-j} + \epsilon_{i,t} \end{aligned} \tag{1}$$

Here, $ret_{i,t}$ denotes the return of stock i on day t. The indicator variable $event_t$ captures the calendar period of interest, such as macro announcement windows, day-of-the-week effects, turn-of-the-month periods, or January trading days.

Following Engelberg et al. (2018), we include several controls to account for short-term return dynamics and market activity. Specifically, we control for ten lags of stock returns, ten lags of volatility (return squared), and ten lags of trading volume. For brevity, we do not report these coefficients. Standard errors are clustered by date.

Table III reports regressions examining how the predictive power of factor signals varies across calendar events. Three main results emerge. First, the coefficient on *Net* is positive and highly significant in all specifications, confirming that the aggregated factor signal strongly predicts cross-sectional returns. During non-event periods, the coefficient on *Net* ranges from approximately 35,000 to 56,000 across specifications. Given that the standard deviation of *Net* is 9.75×10^{-5}, a one–standard-deviation increase in *Net* predicts approximately 3.5 to 5.5 basis points higher factor returns. This confirms that the aggregated factor signal has economically meaningful predictive power in the cross-section.

Second, the interaction terms between *Net* and several calendar indicators—such as Fridays, January trading days, turn-of-the-month (TOM) periods, and macro announcement windows—are negative and statistically significant, indicating that the predictive power of factor signals weakens during these periods. For example, the coefficient on $Net \times Friday$ is −55,604, which almost completely offsets the baseline *Net* coefficient of 56,462, implying that factor predictability largely disappears on Fridays. Similarly, factor predictability declines sharply in January (−79,585), during turn-of-the-month periods (−31,568), and during macro announcement windows (−15,132). These magnitudes imply reductions of roughly 55–100% in the predictive power of factor signals during these calendar windows.

Third, the event dummy coefficients are positive for the high-market windows (Fridays, January, turn-of-the-month, and macro periods) and negative for Mondays, implying that average stock returns are higher (lower) on these dates relative to non-event days, consistent with the well-documented calendar patterns in aggregate returns. Taken together, these results suggest that factor signals become less informative precisely during the well-known calendar windows when aggregate market returns are unusually strong.

To understand whether the reversed calendar effects are driven primarily by the *Long Leg*, or the *Short Leg*, or both, of factor portfolios, we decompose the aggregate factor signal into its positive and negative components. Specifically, we define

$$Long\ Leg = \max(0, Net)$$

and

$$Short\ Leg = \min(0, Net)$$

The variable *Long Leg* therefore captures the positive component of the factor signal, while

Table III
Factor Returns on Calendar Events

This table reports results from a regression of daily returns on calendar events, the *Net* factor variable, calendar event dummy variables, interactions between *Net* and the event variables, and control variables (coefficients unreported). Daily return, the dependent variable, is in basis points. The control variables include lagged values for each of the past 10 days of stock returns, stock returns squared, and trading volume. To create the *Net* factor variable, we use the 153 cross-sectional factors studied in Jensen, Kelly, and Pedersen (2023). For each stock-month observation, we create *Long* and *Short* by summing the stock's weights in the long sides and short sides of the 153 factor portfolios. *Net* is equal to *Long* minus *Short*. We then merge this monthly data set with daily stock return data from CRSP and with daily indicators for calendar events. Standard errors are clustered by date. t-statistics are in parentheses. The sample period is June 1992 to December 2024. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monday	Friday	January	TOM	Macro	Macro Window
Net	35,565***	56,462***	51,603***	48,483***	47,596***	51,142***
	(10.02)	(15.37)	(15.80)	(14.75)	(13.65)	(12.04)
Net × Monday	51,975***					
	(4.74)					
Monday	−13.32***					
	(−3.76)					
Net × Friday		−55,604***				
		(−5.91)				
Friday		13.88***				
		(4.71)				
Net × Jan			−79,585***			
			(−4.80)			
Jan			15.53***			
			(3.53)			
Net × TOM				−31,568**		
				(−2.48)		
TOM				16.49***		
				(4.05)		
Net × Macro					−12,551	
					(−1.20)	
Macro					13.50***	
					(3.93)	
Net × Macro Window						−15,132*
						(−1.81)
Macro Window						8.43***
						(3.15)
Observations	41,659,031	41,659,031	41,659,031	41,659,031	41,659,031	41,659,031
R-squared	0.013	0.013	0.013	0.013	0.013	0.013
Lagged Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm

Short Leg captures the negative component. We estimate the following regression:

$$\begin{aligned} ret_{i,t} = \alpha_i &+ \beta_1 Long\_Leg_{i,t} + \beta_2 Long\_Leg_{i,t} \times event_t + \beta_3 Short\_Leg_{i,t} \\ &+ \beta_4 Short\_Leg_{i,t} \times event_t + \beta_5 event_t \\ &+ \sum_{j=1}^{10} \gamma_j ret_{i,t-j} + \sum_{j=1}^{10} \delta_j ret^2_{i,t-j} + \sum_{j=1}^{10} \rho_j volume_{i,t-j} + \epsilon_{i,t} \end{aligned} \tag{2}$$

The indicator variable $event_t$ captures the calendar period of interest. Controls are included to account for short-term return dynamics and market activity following Engelberg et al. (2018), whose coefficients are not reported for brevity.

Table IV decomposes the factor signal *Net* into its *Long Leg* and *Short Leg* components to examine their respective contributions to the reversed calendar effects. Both *Long Leg* and *Short Leg* significantly predict returns, confirming that each side of the factor signal contains predictive information.

The interaction terms show that during several calendar periods—such as Fridays, January trading days, and macro announcement windows—the predictive power of both legs weakens. For example, on Fridays, the predictive power of the *Long Leg* declines by roughly 210% relative to non-event days (interaction −75,658 relative to a baseline of 36,162), while the predictive power of the *Short Leg* declines by about 44% (interaction −34,730 relative to a baseline of 78,456). A similar pattern appears in January, where the predictive power of the *Long Leg* falls by about 365%, while that of the *Short Leg* declines by roughly 64%. During macro announcement windows, the predictive power of the *Long Leg* decreases by about 34%, while that of the *Short Leg* declines by approximately 28%. These results indicate that both legs contribute to the weakening of factor predictability during these calendar periods.

An exception occurs during turn-of-the-month (TOM) periods. While the predictive power of the *Long Leg* declines sharply—by roughly 267% relative to its baseline (−76,803 interaction relative to 28,759)—the *Short Leg* interaction is positive, representing an increase

Table IV
Long and Short Factor Returns on Calendar Events

This table reports results from a regression of daily returns on the *Long Leg* and *Short Leg*, calendar event dummy variables, interactions between *Long Leg* and *Short Leg* and the calendar event variables, control variables (coefficients unreported), and calendar events. Daily return, the dependent variable, is in basis points. The controls include lagged values for each of the past 10 days of stock returns, stock returns squared, and trading volume. To create the Long Leg and Short Leg variables, we decompose the aggregate factor signal into its positive and negative components: $Long\ Leg = \max(0, Net)$ and $Short\ Leg = \min(0, Net)$. We then merge this monthly dataset with daily stock return data from CRSP and with daily indicators for calendar events. The sample period is June 1992 to December 2024. Robust standard errors are used. t-statistics are in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monday	Friday	January	TOM	Macro	Macro Window
Long Leg	8,228***	36,162***	30,183***	28,759***	21,782***	23,938***
	(6.17)	(26.64)	(23.73)	(22.41)	(16.39)	(16.10)
Short Leg	64,886***	78,456***	74,765***	69,867***	75,336***	80,338***
	(31.18)	(37.04)	(37.37)	(34.61)	(36.24)	(34.77)
Monday	−14.60***					
	(−45.94)					
Monday × Long Leg	68,116***					
	(23.48)					
Monday × Short Leg	35,164***					
	(8.14)					
Friday		15.47***				
		(52.05)				
Friday × Long Leg		−75,658***				
		(−27.93)				
Friday × Short Leg		−34,730***				
		(−8.69)				
January			17.90***			
			(40.12)			
January × Long Leg			−110,241***			
			(−26.68)			
January × Short Leg			−47,583***			
			(−7.80)			
TOM				20.06***		
				(49.25)		
TOM × Long Leg				−76,803***		
				(−20.56)		
TOM × Short Leg				15,503***		
				(2.84)		
Macro					12.86***	
					(40.00)	
Macro × Long Leg					−4,404	
					(−1.49)	
Macro × Short Leg					−21,047***	
					(−4.86)	
Macro Window						7.87***
						(31.34)
Macro Window × Long Leg						−7,997***
						(−3.48)
Macro Window × Short Leg						−22,578***
						(−6.67)
Observations	41,659,040	41,659,040	41,659,040	41,659,040	41,659,040	41,659,040
R-squared	0.013	0.013	0.013	0.013	0.013	0.013
Lagged Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm

of about 22% relative to the baseline *Short Leg* coefficient. This implies that short-leg stocks perform better during TOM days, partially offsetting the decline in the long side. However, the large deterioration in the *Long Leg* dominates, resulting in an overall weakening of factor predictability.

III. Discussion

In this section we discuss potential channels of the reversed calendar effects of factor returns. We focus our discussion on distinguishing whether the patterns reflect data mining or sentiment-driven mispricing.

A. Data Mining

To test the data-mining explanation, we compute factor returns using strictly out-of-sample data for each factor. Specifically, for each factor we classify calendar years as in-sample if they fall within the factor's original sample period, as recorded in Jensen, Kelly, and Pedersen (2023), and as out-of-sample otherwise. The in-sample (out-of-sample) aggregate portfolio then averages, on each day, only the factors whose original sample includes (excludes) that year.

From Table V, we can see the reversed calendar effects become slightly weaker in the out-of-sample period, largely reflecting the general decline in factor returns after publication, consistent with the findings of McLean and Pontiff (2016), who document that factor returns tend to diminish following their discovery. Nevertheless, the reversed calendar patterns remain economically large and statistically significant. In the out-of-sample period, factor returns are 7.63 bps lower overnight than intraday ($t = -7.82$). Similarly, factor returns are 1.06 bps lower on Fridays than on midweek days ($t = -3.65$), which are in turn 1.44 bps lower than on Mondays ($t = -5.83$). At the monthly horizon, factor returns are 3.02 bps lower in January than in other months ($t = -3.53$). During turn-of-the-month periods,

Table V
Average Daily Returns (bps) of Factors In-Sample vs. Out-of-Sample

This table summarizes and compares the calendar effects of factor returns in-sample vs. out-of-sample. We report the average daily returns across calendar events (non-events) that we study. We create our factor portfolio by equally aggregating the 153 factors studied by Jensen, Kelly, and Pedersen (2023). The upper panel shows the results for the equal-weighted aggregate factor portfolio. The middle and lower panel show the results for the aggregate factor portfolio using in-sample and out-of-sample data, respectively. The Macro Window column aggregates the 3-day windows of FOMC, GDP, NFP, and ISM announcements. Average daily returns are in basis points. Two-sample t-tests are conducted within each calendar group. t-statistics are in parentheses. We use CRSP U.S. daily stock return data from June 1992 to December 2024. *, **, *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

	Overnight	Intraday	Friday	Mid-Week	Monday	Jan	Non-Jan	Turn-of-Month	Non-TOM	Macro Window	Non-Macro
153 Factors Average	−2.01	5.45	1.24	3.44	5.77	0.22	3.71	1.89	3.61	2.99	3.71
Difference	−7.46***		−2.20***			−3.49***		−1.72***		−0.72***	
	(−8.54)		(−5.34)			(−3.66)		(−6.01)		(−4.62)	
					−2.33***						
					(−7.06)						
In-Sample	−2.11	6.27	0.03	4.36	7.85	−0.06	4.52	2.35	4.36	3.69	4.45
Difference	−8.39***		−4.33***			−4.58***		−2.01***		−0.76***	
	(−5.93)		(−5.18)			(−3.32)		(−5.22)		(−3.99)	
					−3.49***						
					(−5.05)						
Out-Of-Sample	−2.14	5.49	2.23	3.29	4.73	0.57	3.59	1.93	3.50	2.71	3.74
Difference	−7.63***		−1.06***			−3.02***		−1.57***		−1.03***	
	(−7.82)		(−3.65)			(−3.53)		(−5.46)		(−4.82)	
					−1.44***						
					(−5.83)						

Note: For the day-of-the-week horizon, the first difference row is Friday vs. mid-week and the second is mid-week vs. Monday. The overnight-vs.-intraday comparison uses a paired t-test.

factor returns are 1.57 bps lower than on non–turn-of-the-month days ($t = -5.46$). Finally, during macro announcement windows, factor returns are 1.03 bps lower than on non-macro days ($t = -4.82$).

These results suggest that the reversed calendar effects cannot be fully explained by data mining. Moreover, the persistence of these effects out of sample is consistent with investor learning about mispricing, whereby arbitrage capital gradually attenuates—but does not completely eliminate—the abnormal returns associated with these calendar patterns.

B. Sentiment-driven Mispricing

Behavioral models suggest that investor sentiment and attention fluctuate over time and may be systematically linked to calendar events such as month-ends, macroeconomic announcements, or periods of heightened market activity. During such periods, sentiment-driven demand for certain stocks may temporarily distort prices, generating predictable patterns in factor returns across calendar windows.

To proxy for investor sentiment, we use the Daily News Sentiment Index (DNSI) provided by the Federal Reserve Bank of San Francisco. The DNSI is constructed using textual analysis of a large set of U.S. newspaper articles. Specifically, the index measures the tone of economic news by applying natural language processing techniques to articles published in major U.S. newspapers, identifying positive and negative sentiment related to economic conditions. The resulting index provides a high-frequency measure of daily sentiment regarding the economic outlook.

An advantage of the DNSI is that it captures time-varying sentiment and attention in real time, allowing us to study how fluctuations in news sentiment interact with the predictive power of factor signals. Because the index is available at the daily frequency, it is particularly well suited for our analysis of calendar effects in factor returns.

We incorporate a daily news-based sentiment index into our regressions:

$$
\begin{aligned}
ret_{i,t} = \alpha_i &+ \beta_1 Net_{i,t} + \beta_2 Net_{i,t} \times event_t \times sentiment_t + \beta_3 event_t + \beta_4 event_t \times sentiment_t \\
&+ \beta_5 Net_{i,t} \times sentiment_t + \beta_6 Net_{i,t} \times event_t + \beta_7 sentiment_t \\
&+ \sum_{j=1}^{10} \gamma_j ret_{i,t-j} + \sum_{j=1}^{10} \delta_j ret^2_{i,t-j} + \sum_{j=1}^{10} \rho_j volume_{i,t-j} + \epsilon_{i,t} \qquad (3)
\end{aligned}
$$

The results show that news sentiment strongly conditions the calendar patterns in factor predictability. Unconditionally, factor predictability is higher on high-sentiment days: the coefficient on $Net \times Sentiment$ is positive and significant in all specifications. Conditional on the calendar windows, however, elevated sentiment significantly amplifies the erosion of factor predictability. For example, the triple interaction term $Net \times Friday \times Sentiment$ is $-125{,}434$ ($t = -12.06$), indicating that high sentiment further reduces factor predictability on Fridays. Similarly, the coefficient on $Net \times January \times Sentiment$ is $-40{,}117$ ($t = -2.66$), suggesting that elevated sentiment significantly amplifies the erosion of factor predictability in January. A comparable pattern appears for turn-of-the-month periods, where $Net \times$

$TOM \times Sentiment$ equals −37,983 ($t = -2.61$), as well as for macro announcement days (−89,061, $t = -7.77$) and macro announcement windows (−21,927, $t = -2.43$). The Monday triple interaction is instead positive (66,834, $t = 5.72$), mirroring the fact that Monday is a high–factor-return day. These results indicate that high sentiment intensifies the calendar-related variation in factor profitability.

This finding suggests that periods of high sentiment are associated with a greater erosion of factor profitability, which points to a consistent behavioral interpretation. Periods associated with strong calendar effects—such as certain days of the week, month-end trading, or major announcement windows—may coincide with heightened investor attention and sentiment, which increases demand for popular or speculative stocks and compresses the return spread captured by factor strategies. Anecdotal evidence from episodes such as the surge in meme stock trading, where retail investors aggressively bid up highly visible stocks and inflicted losses on hedge funds with short positions, provides a recent illustration of how sentiment-driven demand can temporarily overwhelm fundamental signals and weaken the profitability of factor-based strategies.

IV. Conclusion

A large literature documents systematic calendar patterns in the U.S. equity premium. Stock returns are found to be higher overnight, on Fridays, in January, around the turn of the month, and during major macroeconomic announcement periods such as FOMC, GDP, NFP, and ISM releases. In this paper, we examine how factor portfolios behave during these calendar periods.

Using a comprehensive set of 153 long–short factor portfolios, we document a striking pattern: factor premia are lower during precisely the same periods when the equity premium is unusually high. This finding reveals a systematic reversed calendar effect in factor returns. Further decomposition shows that both the long and short legs contribute to this

Table VI
Factor Returns and Sentiment on Calendar Events

This table reports results from a regression of daily returns on calendar events, the *Net* factor variable, calendar event dummy variables, interactions between *Net* and the event variables, and control variables (coefficients unreported). Daily return, the dependent variable, is in basis points. The control variables include lagged values for each of the past 10 days of stock returns, stock returns squared, and trading volume. To create the *Net* factor variable, we use the 153 cross-sectional factors studied in Jensen, Kelly, and Pedersen (2023). For each stock-month observation, we create *Long* and *Short* by summing the stock's weights in the long sides and short sides of the 153 factor portfolios. *Net* is equal to *Long* minus *Short*. *Sentiment* is the Daily News Sentiment Index of the Federal Reserve Bank of San Francisco. Each specification includes the event dummy, *Sentiment*, *Net*, all pairwise interactions, and the triple interaction $Net \times event \times Sentiment$. We then merge this monthly data set with daily stock return data from CRSP and with daily indicators for calendar events. Robust standard errors are used. t-statistics are in parentheses. The sample period is June 1992 to December 2024. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

	Monday	Friday	January	TOM	Macro	Macro Window
Net	35,278***	55,182***	50,865***	47,785***	46,545***	50,205***
	(35.91)	(55.29)	(54.01)	(50.10)	(47.50)	(46.44)
Sentiment	4.75***	9.70***	4.17***	9.20***	5.26***	1.65***
	(9.08)	(18.02)	(8.19)	(18.14)	(10.03)	(2.82)
Net × Sentiment	34,109***	70,974***	61,646***	50,882***	63,093***	55,043***
	(7.01)	(14.09)	(13.09)	(10.80)	(12.89)	(10.04)
Monday	−14.17***					
	(−66.76)					
Net × Monday	50,169***					
	(25.45)					
Monday × Sentiment	16.01***					
	(13.52)					
Net × Monday × Sentiment	66,834***					
	(5.72)					
Friday		14.33***				
		(73.53)				
Net × Friday		−52,539***				
		(−29.03)				
Friday × Sentiment		−8.55***				
		(−8.01)				
Net × Friday × Sentiment		−125,434***				
		(−12.06)				
January			13.44***			
			(41.44)			
Net × January			−80,023***			
			(−26.38)			
January × Sentiment			17.87***			
			(11.76)			
Net × January × Sentiment			−40,117***			
			(−2.66)			
TOM				17.35***		
				(64.47)		
Net × TOM				−30,681***		
				(−12.28)		
TOM × Sentiment				−16.30***		
				(−10.96)		
Net × TOM × Sentiment				−37,983***		
				(−2.61)		
Macro					12.80***	
					(60.25)	
Net × Macro					−10,255***	
					(−5.20)	
Macro × Sentiment					14.16***	
					(12.12)	
Net × Macro × Sentiment					−89,061***	
					(−7.77)	
Macro Window						7.64***
						(46.09)
Net × Macro Window						−14,287***
						(−9.29)
Macro Window × Sentiment						16.37***
						(17.85)
Net × Macro Window × Sentiment						−21,927**
						(−2.43)
Observations	41,659,040	41,659,040	41,659,040	41,659,040	41,659,040	41,659,040
R-squared	0.013	0.013	0.013	0.013	0.013	0.013
Lagged Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm

pattern—with the long leg deteriorating more in most calendar windows—indicating that the weakening of factor profitability during these calendar windows reflects a broad compression of cross-sectional return spreads rather than movements confined to one side of the portfolio.

We consider two potential explanations for these findings: data mining and mispricing. To distinguish between data mining and mispricing, we conduct out-of-sample tests and find that the reversed calendar effects remain economically large and statistically significant, even though factor returns decline following publication. These results suggest that data mining alone cannot fully account for the observed patterns.

Finally, we incorporate a daily news sentiment index to explore the role of investor sentiment. We find that the reversed calendar effects become stronger when news sentiment is high, indicating that elevated sentiment further weakens the predictive power of factor signals during these periods. This evidence is consistent with sentiment-driven mispricing, whereby heightened investor attention and optimism distort prices and compress the return spreads captured by factor strategies.

Overall, our results provide new evidence that factor returns exhibit systematic calendar patterns that are the reverse of those observed in the aggregate market. These findings highlight the importance of investor sentiment and attention in shaping the time variation of factor profitability and contribute to a better understanding of the mechanisms underlying return predictability in financial markets.

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