New Avenues in Expected Returns: Investor Overreaction and Overnight Price Jumps in US Stock Markets

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Abstract

Using 9,283 stocks listed on NYSE, AMEX, and NASDAQ, we analyze overnight price jumps and report short-term investor overreaction to information shocks, and document return reversal and predictability for up to five days. For negative and positive overnight jumps, results are significant and robust to various model specifications. In the cross-section, the degree of reversal is considerably larger for stocks that are less costly to arbitrage. In contrast to this overreaction, a zero-cost contrarian trading strategy with extreme decile portfolios -shaped according to lagged jump returns- incurs 0.6% of risk-adjusted loss in a 1-month investment horizon. Together, these connote that documented overreaction and return reversal are short-term market phenomena. The novel findings for jump stocks also build a new avenue for overnight and intraday expected returns in the recently renowned *tug of war* literature which relies on investor heterogeneity. We show that jump stocks have significantly different abnormal returns than non-jump stocks in both overnight and intraday components for the next month. Our study stands at the intersection of overreaction, jump, and return predictability literature by paying special attention to investor behaviors around price discontinuities and post-shock return dynamics.

JEL classification: G10; G11; G12; G14; G40

Keywords: Price Jumps; Investor Overreaction; Return Predictability; Costly Arbitrage

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1 Introduction

Instant and precise reflection of new information to prices in a friction-free market has been one of the asset pricing mantras for decades. Also linked to this *frictionless markets* parlance, there should be no predictability in returns following shocks, be they news-induced or not (Frank and Sanati (2018)). Nevertheless, this assertive textbook approach is not a proper description of market practice as the prices do not completely embody the information available to participants at a given time. The literature extensively documents drifting as well as reversing return patterns in the wake of information arrival. In one strand of the literature, these predictable patterns are linked to flaws in investors' cognitive judgments and to market inefficiency while other line of research ties this return behavior to varying levels of expected returns as a rational reaction to fluctuating risk levels (see Lehmann (1990), Fama (1991), Chopra et al. (1992) and McLean and Pontiff (2016) among many others). Beyond these discussions however, a panoramic picture of overreaction and underreaction studies exhibits that the literature is still indecisive about the dominant return patterns in the post-shock period as highlighted in Frank and Sanati (2018) and Tetlock (2014). We contribute to these discussions with a special focus on overnight price jumps and follow-up return dynamics driven by investors' overreaction to positive and negative overnight information shocks.

Ranging from three to five years of cycles to time spans of minutes during a specific trading day, varying return patterns over different investment horizons have been surfaced in association with investor overreaction and its reciprocal interaction with expected returns. Guided by the experimental psychology on people's inclination to overreact to information shocks, De Bondt and Thaler (1985) report that a portfolio of stocks with prior losses in the preceding three-to-five years outperforms the portfolio of stocks with earlier gains. Chopra et al. (1992) later confirm overreaction and long-run reversals with additional adjustments for size and volatility around earnings announcements and attract the attention to clientele effect for this overreaction pattern. Along with that, Avramov et al. (2006), Lo and MacKinlay (1990), Lehmann (1990), Poterba and Summers (1988) and Barr Rosenberg and Lanstein (1998) among others report overreaction and return reversal also for shorter time windows. In the context of overnight price jumps and follow-up return characteristics, however, the overreaction literature has remained untouched to date. Similar to this latter group of studies, our work stands under the umbrella of short-term overreaction research and fills that void.

The finance literature has extensively considered extreme price changes over the past decades and implications for price discontinuities have been widely studied for single assets, portfolios, and derivative instruments. Incorporation of extreme price movements to asset pricing dates back to Press (1967) in which the long-tailed, non-Gaussian return distributions are modeled with compound Poisson process. Ever since its recognition as a critical determinant, price jumps have been studied in a myriad of ways: amendments in asset pricing (Merton (1976); Beckers (1981); Ball and Torous (1983); Ball and Torous (1985); Câmara (2009)), return predictability (Jiang and Yao (2013); Jiang and Zhu (2017)), information flow (Barclay and Litzenberger (1988); Kim and Mei (2001); Andersen et al. (2007); Bollerslev et al. (2008); Baker et al. (2021); Jeon et al. (2022)), liquidity shocks (Jiang et al. (2011); Christensen et al. (2014)) and overreaction/underreaction (Kaul and Nimalendran (1990); Jiang and Zhu (2017)) are a few of the concepts analyzed in connection with jumps in stock prices.

Using the methodology of Lee and Mykland (2008), we first detect overnight price jumps in stocks listed on NYSE, AMEX, and NASDAQ over the entire July 1993 - December 2021 period or in-between. Like Jiang and Zhu (2017), we use jumps as a proxy for information shocks that trigger investor overreaction and lead to breaks in the price path. After specifying the dates with price discontinuities, we keep subsequent returns under the magnifying glass for up to five days to assess the repercussions of investor overreaction. With monthly accumulated figures, we show a clear overreaction pattern to unexpected overnight information flow in both positive and negative states and report statistically and economically significant return predictability for the post-shock period. A contrarian trading strategy based on monthly jump figures further evinces that these overreactions and return reversals are short-term market episodes. Moreover, cross-sectional analysis unravels distinctive overreaction dynamics for stocks with different idiosyncratic risks. In their influential paper, Lou et al. (2019) report that higher overnight returns in a month are followed by higher overnight and lower intraday returns in subsequent months. We replicate the main results of Lou et al. (2019) separately for jump and non-jump stocks. Though our analysis shows quite similar results for non-jump stocks, we document significantly different findings for jump stocks. In that regard, our study opens up a new avenue in overnight and intraday expected returns. On the whole, our contribution to extant literature will be twofold.

First, our study concentrates on an unexplored question and connects overnight price jumps and their reversals with short-term overreaction discussions in stock markets. Jiang and Zhu (2017) provide evidence of underreaction to information shocks which end up as daily jumps whereas we analyze extreme price movements that become ephemeral to a certain extent after the market correction. As opposed to Jiang and Zhu (2017) which identify daily jumps and decompose these close-to-close returns into their overnight and intraday components, we detect overnight jumps in its own time series and mark the days with overnight return surprise. Our filtering methodology provides us with special information when there is no daily jump. We additionally run our detection test for close-to-close returns to see jumps in daily price movements and their alignment with overnight jumps. Strikingly, only 11.6% percent of overnight jump days have also jumps in daily returns. That said, this argument does not imply any straightforward return level comparison since jumps are relative magnitudes in the local neighborhood of return time series. For instance, 2% overnight return may be marked as a jump whereas 2% close-to-close return may not be. In short, this study extends our understanding of price behaviors directly after overnight shocks.

We further document the results of contrarian and relative strength trading strategies to see if the winners (stocks with cumulative positive jump returns in the previous month) will be the losers within the one-month investment horizon or vice versa. However, shorting the stocks in the highest decile and buying the stocks with the most negative jump figures ended up in a statistically significant 0.6% loss. In the same fashion, short and long trading strategies respectively in the highest and lowest decile portfolios do not result in any risk-adjusted gain. These pricing behaviors imply that overreaction and return reversal after overnight jumps are short-term market phenomena. Inspired by the work of Atilgan et al. (2020), we also look at costly arbitrage conditions and cross-sectional variation in jump and reversal levels to further unearth differing pictures in different stock groups. With focal attention to reversed jump fraction, we show that arbitrageurs are less eager for a price correction in stocks with high idiosyncratic risks whereas roughly 51% and 40% of jump magnitudes are reversed back for stocks with the lowest idiosyncratic risk figures respectively after negative and positive jumps in the first day. In that sense, our study provides novel explanations for why overreaction in some stocks becomes more stagnant compared to some other equities.

Second, we contribute to the literature on return predictability studies steered by investor heterogeneity and overnight returns. Lou et al. (2019) are the first who tie overnight and intraday components of returns to predictability and investor heterogeneity. Akbas et al. (2022) later look at these empirical findings from a different angle with a profound analysis of the "tug of war" intensity during a month. As opposed to Lou et al. (2019) which accumulate all overnight returns in their return predictability analysis, we calculate monthly cumulative jump returns to pay particular attention to stocks only with overnight information shocks. This way, we keep investor reactions under magnifying glass around jumps and gauge the return predictability for jump stocks. As a matter of fact, our approach reveals a new story and brings in another perspective to this return predictability in the light of extreme price movements. Succinctly, we show that abnormal returns in overnight and intraday returns with a one-month horizon are significantly different for jump stocks compared to non-jump equities. We document that a zero-cost portfolio trading strategy results in 3.9% less risk-adjusted return for the overnight return component when stocks are sorted according to their monthly cumulative overnight returns although the same strategy ends in 4.4% less risk-adjusted loss for the intraday return component. Also strikingly, main *tug of war* patterns reported in Lou et al. (2019) are broken for jump stocks in the lowest decile when stocks are sorted according to their overnight return components. We also document that *tug of war* phenomenon is intensified for all strategies when stocks are ordered according to their lagged intraday return components.

The rest of the paper is organized as follows. Section 2 presents the related literature, contrasts our study with the previous research, and includes some additional notes on the clientele effect and information quality. In Section 3, we provide the details of data and filtering mechanisms together with the applied methodology for jump identification and time series construction. Section 4 is reserved for empirical findings. Implications for market participants and theoretical foundations are detailed in Section 5. Section 6 concludes.

2 Relevant Literature

Broadly, our study stands at the intersection of jump, overreaction, and return predictability literature. Among others, the noteworthiness of jump returns is highlighted by Kapadia and Zekhnini (2019) who document that the yearly return of a stock is cumulatively made of the price jumps in 4 days over a year, and by Jiang and Yao (2013) who analyze intermittent jumps triggered by information shocks over a large horizon and document that return predictability associated with firm characteristics owes too much to price jumps such that size, value, and liquidity measures lose their predictive power once the extreme price movements are controlled.

Literature on the overnight jump returns and investor overreaction is relatively intact and the closest study to ours is Jiang and Zhu (2017) in which authors rather study underreaction to information shocks. Used as a proxy for information shocks, jumps in Jiang and Zhu (2017) are analyzed in the context of short-term underreaction in US equity markets in which the analysis rests on daily jump detection and decomposition of it into overnight and intraday sections. Firm-specific news is generally disclosed after the closing bell and priced in largely by individual investors as trading commences in the next morning (Lou et al. (2019)). Moreover, the main driving force of overnight returns is the information available to market participants (Jones et al. (1994); Barclay and Hendershott (2003); Barardehi et al. (2022) among others). Though not regarding price jumps, another recent study due to Atilgan et al. (2020) shows that investors do not optimally interpret the content of negative news and underreact to it. They over-demand the stocks with recent extreme losses which creates left-tail momentum. To put it differently, their study is crucial in uncovering a new empirical fact that anomalously contradicts the *higher risk - higher return* premise. Since the essence of their study is also tied to substantial negative returns, we contrast our study with theirs both methodologically and implication-wise.

The impact of overnight periods on stock price behaviors has also attracted substantial interest over decades. Among early works, Amihud and Mendelson (1987) show that open-to-open returns in Dow Jones Industrial stocks have higher variance, higher serial dependence, greater peakedness and thicker tails compared to close-to-close returns. This was first attributed to different trading mechanisms in the opening (periodic call market) and closing hours (continuous auction). In their follow-up study, however, Amihud and Mendelson (1991) analyze 50 stocks in Tokyo Stock Exchange in which the Exchange employs two separate periodic call markets both in the morning and afternoon sessions. Authors this time show that higher volatility and negative autocorrelation in open-to-open returns are due to the prior nontrading section over the night and document that price reversals are stronger in the morning session compared to the afternoon period. With a similar interest in the dynamics of intraday and overnight return components, Gerety and Mulherin (1992) show that enhanced trading activity at the opening and closing hours of a typical trading day is positively related to the expected overnight return volatility. Investors abstain from carrying their positions over the night to decrease their risk exposure and that leads to a surge in trading volumes at both ends of the day. Opening volume is also positively correlated with the unexpected volatility component which accounts for the surprise in overnight information flow. Many other similar studies to date have improved our knowledge of ex-post and ex-ante returns for overnight and intraday return components. In their recent epochal research, Lou et al. (2019) show that overnight and intraday returns are mainly driven by the interplay between retail and institutional investors, and that creates a persistent pattern in expected returns. A subsequent study by Akbas et al. (2022) looks at this *tug of war* from a different angle and focuses on the intensity of return reversals during a month. However, extant literature does not conduct separate analyses for jump and non-jump stocks while exploring distinctive patterns in overnight and intraday return components.

Notes on Clientele Effect and the Content of Information

Research on overnight and intraday components of close-to-close daily returns has heralded new avenues for clientele relevance, the content of information, and return predictability. In the asset-pricing context, non-homogeneous investor beliefs and preferences reveal themselves in various forms. Seasonality in returns (Ritter and Chopra (1989); Bogousslavsky (2016)), portfolio rebalancing habits (Calvet et al. (2009); Bianchi (2018), trading preferences (Barber and Odean (2008); Berkman et al. (2012); Lou et al. (2019)), consumption and portfolio formation (Bhamra and Uppal (2014)), overreaction and underreaction in returns (De Bondt and Thaler (1985); Jiang and Zhu (2017); Bianchi (2018); Lou et al. (2019); Akbas et al. (2022)) and shocks in market prices (Jiang and Zhu (2017); Frank and

Sanati (2018)) are some of the empirical findings linked to this heterogeneity. Trading activities of retail and institutional investors are clustered in different portions of a trading day (Barber and Odean (2008); Berkman et al. (2012); Lou et al. (2019) among others). Subject to different market imperfections and prone to different behavioral biases, retail and institutional investors have distinct trading preferences and information processing skills. Shefrin (2008) documents that heterogeneous expectations of individual and professional investors have direct consequences for asset pricing. With their different forecasting rationales, some investors expect the continuation of market returns while other groups anticipate reversals in market trends. The author argues that fat tails in return distributions are a result of pessimist and optimist investors clustered at both ends of the distribution.

Recently, Lou et al. (2019) report a persistent interplay between individual and institutional investors creating predictable return patterns for overnight and intraday components of daily returns even into the sixty-month horizon. Specifically, higher overnight returns in a month are succeeded with higher overnight returns and lower intraday returns in the following months. Overpricing at the outset of a day -driven mostly by retail investors- is reversed by the enhanced trading activities of opposing clientele during the day. To put it differently, trade initiation is relatively more prevalent around the market opening for retail investors while institutional trading is dominant, especially in the second part of the day. This finding is consistent with Berkman et al. (2012) who report that individual investors -after markets open- snap up stocks that grabbed their attention in the previous day and with Barber and Odean (2008) who show how higher returns in the preceding day allure retail investors and make them placed on the buy-side in the next day's opening. In a follow-up study to Lou et al. (2019), Akbas et al. (2022) analyze the monthly "tug of war" intensity and show how higher intensity cross-sectionally predicts higher future returns. The authors conjecture that arbitrageurs undervalue informational content of successively arriving positive overnight returns and attribute these movements falsely to overoptimistic noise trader activity thereby creating an overcorrection picture in stock prices.

The pattern of the information arrival also affects the return dynamics. Da et al. (2014) document that investors pay less attention to successively arriving small amount of information flows whereas they are all ears to the irregularly appearing discrete but influential large amount of information flows. Authors show that momentum returns are more powerful for the former group of stocks with continuous information and returns substantially decrease towards stocks with discrete information. Barardehi et al. (2022) conducts this analysis further with overnight and intraday components of daily returns and they get results consistent with Da et al. (2014).

Epstein and Schneider (2008) document that investors adapt themselves to the worst-case scenarios under poor information quality and react more intensely to bad ambiguous news than they do to ambiguous good news. Similarly, as Gollier (2011) reported, agents put more weight on their worst priors and show high ambiguity aversion during uncertainty. Since the assessment of information quality and level of market and firm-specific ambiguity are not within the scope of this study, we leave this discussion for further research.

3 Data and Methodology

3.1 Data

Since price jumps are low-probability episodes in nature, it is important to keep the database as large as possible.[1] We aim to tackle this rare-event challenge with a large sample of 9,283 stocks listed on NYSE, AMEX, and NASDAQ during the whole July 1993-December 2021 period or in-between. Our daily raw data start as of June 15, 1992, on which the opening prices are first available in the CRSP database and our analyses start as of July 1993 when we first get our returns for the momentum variables along with the full-month jump incidences.

Our data sample consists of the entire CRSP database with some further filters. The study is conducted with common shares that are listed on the main US exchanges (NYSE, AMEX, NASDAQ). We make use of PERMCO and PERMNO as they are the primary CRSP identifiers to track companies and securities over the trading history respectively. In our main analysis, we use PERMCO identifiers that are associated only with one PERMNO over the entire stock records. In the next step, we make sure that there are no trading breaks during the life of the company to abstain from artificial jump identification. Missing opening prices are filled with the previous day's closing prices to ensure the jump detection is not halted. In case an intraday jump is identified on that day, we eliminate it during our

[1] For the significance of sample size in rare event studies, see Jiang and Yao (2013) on jumps and cross-sectional return predictability, Kelly and Jiang (2014) on extreme events and associated tail risk in stock returns and Boyer and Vorkink (2014) on skewness and investors' preferences towards lottery-like assets.

robustness check. If the closing price is missing, CRSP sets the bid-ask average as the closing price on that day. We retain these closing prices in the main analysis as they still reflect some sort of investor judgment about the market price. In our robustness check, however, the jumps whose detection windows include at least one closing price calculated through the bid-ask average are excluded from our results. We keep stocks that have at least three years of trading history and repeat our analysis with stocks that have trading archives longer than two years for robustness check. We do not shorten the data length further to ensure that momentum returns are calculated at least for a cycle of one complete year. As the last data-sifting layer, we filter out observations with missing COMPUSTAT values. After these refinements, we cover 9283 stocks from US markets. Sieved CRSP data are then merged with pertinent firm characteristics data from COMPUSTAT. We follow Fama and French (2008) and Jiang and Zhu (2017) to construct our variables and explain them below in turn.

Size (S): At the end of every June, we calculate market capitalization through the CRSP dataset. It is basically the natural logarithm of the last closing price times outstanding shares.

Book-to-Market Ratio (BM): Book value of the equity is received from the fiscal year ending figures in the previous calendar year while the market value of the equity is calculated at the end of the last trading day in the preceding calendar year. The former is computed from COMPUSTAT by adding deferred taxes and investment tax credits to shareholders' equity and subtracting the preferred stock adjustments. Depending on the availability, preferred stock rectification can be drained -with an order of precedence- through PSTKL or PSTKRV, or PSTK variable codes in COMPUSTAT. For shareholders' equity; SEQ or CEQ+PSTK or AT-LT variable codes can be used in order. TXDITC is the COMPUSTAT variable name for deferred taxes and investment tax credits. Market value of the equity is computed with CRSP data.

Idiosyncratic Volatility (IVOL)[2]: We first run Fama-French three-factor model with daily

[2]In their seminal paper; Ang et al. (2006) report that stocks with high idiosyncratic volatility oddly have lower subsequent returns and this empirical finding has been named as "idiosyncratic volatility puzzle". See Hou and Loh (2016) for a comprehensive recent discussion on present explanations in the literature and the extent this puzzle had been solved thus far.

data frequency and save the regression residuals[3]. Monthly IVOL variables are created by calculating the standard deviations of these residuals over each separate period.

Illiquidity (AI): We use Amihud Illiquidity due to Amihud (2002) and it is the absolute daily return divided by daily trading volume in dollars. To calculate dollar trading volumes, we use the mid-point of the daily high-low range as the proxy multiplier. We control for illiquidity since it has been documented that expected excess stock returns embed some level of illiquidity premium. Following Jiang and Zhu (2017), we modify NASDAQ volume figures by multiplying them by 0.7.[4] This is to make trading volumes comparable across the stock exchanges since NYSE and AMEX are mostly centralized auction markets where customer orders directly interact with each other although NASDAQ is less-centralized with fragmented dealer market formation and volume counting procedure compelled by Securities and Exchange Commission (SEC) inflates the figures in this Exchange.

Momentum (MOM): It is the buy-and-hold return over an 11-month horizon backwards with the preceding month skipped. Following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), we split it into two in the following manner during our analysis: $(t-1, t-5), (t-6, t-11)$.

Leverage (LEV): Leverage variable is constructed by taking the natural logarithm of the ratio of total assets' book value on the fiscal year ending month in the preceding calendar year to market equity figures at the end of December in again the previous calendar year.

Previous Day Return (PREV): This variable is constructed to control for the information flow in the day preceding the overnight jumps. It is the monthly-cumulated daily returns prior to jumps.

[3]The regressor factors are taken from Kenneth French's website.

[4]This adjustment factor is originally based on an SEC report on "order executions across equity market structures". See footnote 16 in the following link to that report https://www.sec.gov/pdf/ordrxmkt.pdf

3.2 Methodology

3.2.1 Jump Identification

We model stock prices with a semi-martingale process embodying both diffusive continuous movements and jump components. Let X_t stand for the price process of a stock in a probability space with available information set $\mathcal{F}_t$ to all parties. For a unit period of [0,T] ($T \geq 0$), it is a convention to specify Ito semi-martingale process with price discontinuities as in the following jump-diffusion model:

$$X_t = X_0 + \int_0^t \mu_s d_s + \int_0^t \sigma_s dB_s + \sum_{k=1}^{N_j^t} J_i \quad ; \quad \forall t \in [0, T] \tag{1}$$

where the first three terms ($X_0 + \int_0^t \mu_s d_s + \int_0^t \sigma_s dB_s$) constitute continuous stochastic price path with initial price (X_0), drift term (μ), diffusive variance (σ) and standard Brownian motion (B). The last summation term injects the random price jumps into the model with counting process N_j and jump sizes $J = J_k$ for $k = 1, 2, ..., N_j^t$.

With equally spaced observations at times $t_0 < t_1 ... < t_{n-1} < t_n$ over the period $[0,\ T]$, one can calculate M distinct returns. Let $r_{m_i} = Y_{t_{i+\xi}} - Y_{t_i}$ be the return for an interval in which ξ determines the length of return intervals $\forall m \in\ [1,\ M]$ and $\forall \xi\ \in\ [0,\ T]$. Asymptotically, as ξ gets narrower, realized variance converges to quadratic variation. Furthermore, integrated volatility is detached from total quadratic variation via the realized bi-power variation due to Barndorff-Nielsen and Shephard (2004). It is also customary to link bi-power variation to realized variance to disentangle the jump variation. Specifically,

$$RV_T = \sum_{i=1}^{M} |r_{m_i}|^2 \quad \text{and} \quad \lim_{\xi \to 0} RV = QV = \int_0^t \sigma_s^2 ds \ + \sum_{i=0 \leq s \leq t} \Delta Y_s^2 \tag{2}$$

$$BV = \frac{\pi}{2} \frac{M}{M-1} \sum_{i=2}^{M} |r_{m_i}| \left| r_{m_{i-1}} \right| \quad \text{and} \quad \lim_{\xi \to 0} BV = IntV = \int_0^t \sigma_s^2 ds \tag{3}$$

where ΔY stands for instant log-price changes due to jumps and RV, QV, BV and $IntV$ are respectively the realized variance, quadratic variation, bi-power variation, and integrated volatility. The terms $\frac{\pi}{2}\frac{M}{M-1}$ in bi-power variation act as a standardization factor (see Barndorff-Nielsen and Shephard (2003) for further discussion and Huang and Tauchen

(2005) for extensions). Herewith, the jump variation component and its relative contribution to quadratic variation are straightforward in the following forms:

$$JV = RV - BV \quad \text{and} \quad \lim_{\xi \to 0} JV = \sum_{k=1}^{N_j^t} J_i \tag{4}$$

in which JV is the variation due to jumps.

We use a non-parametric method that simply isolates integrated volatility from total quadratic variation in return series thereby determining the contribution of jumps to total variation. Among many others, Barndorff-Nielsen and Shephard (2006), Jiang and Oomen (2008), Lee and Mykland (2008) document non-parametric tests for jump identification. At first glance, quantifying jump-variation as in Barndorff-Nielsen and Sheppard (BNS) approach already seems sufficient for jump detection. However, Lee and Mykland (2008) document flaws in detection rates for BNS test during low and high variance periods. This is also valid for the Jiang and Oomen (JO) test which rests on a variance swap replicating strategy instead of bi-power variation. Also, Dumitru and Urga (2012) compare alternative non-parametric jump tests and authors report the techniques that are offered by Andersen et al. (2007) and Lee and Mykland (2008) to be the best-performing ones.

Let $\mathcal{L}_i$ be the test statistic for jump identification in Lee and Mykland (2008). In essence, it dissipates the concern for classifying a large return as a jump when it is essentially due to higher volatility during the period in question (and vice versa). Hence, $\mathcal{L}_i$ is formed as a standardized return metric in which the standardization is achieved by dividing each return with the square root of the accompanying integrated volatility.

$$\mathcal{L}_i = \frac{r_{m_i}}{\sqrt{IntV_{LM}}} \quad \text{with} \quad IntV_{LM} = \frac{\pi}{2} \frac{1}{M-2} \sum_{j=i-M+1}^{i-1} \left| r_{m_j} \right| \left| r_{m_{j-1}} \right| \tag{5}$$

where $IntV_{LM}$ stands for integrated volatility in Lee and Mykland (2008). Authors show that when there is no jump, the asymptotic distribution of $\mathcal{L}_i$ is a standard normal whereas the presence of jumps leads to elevated test statistics. They offer the below metric to decide whether to reject the no-jump hypothesis or not. Variation in returns is due to jump if,

$$\frac{max_{i \in \bar{A}_n} |\mathcal{L}_i| - C_n}{S_n} > \delta \tag{6}$$

where C_n and S_n are in the following mathematical notation with n being the number of observations and $c = \sqrt{2/\pi}$. The critical value is $\delta = -ln[-ln(1 - \alpha)]$ in which α is the significance level. The window size K at the jump detection time is taken 16 as recommended in Lee and Mykland (2008) for daily datasets.

$$C_n = \frac{[2ln(n)]^{1/2}}{c} - \frac{ln4\pi + ln[ln(n)]}{2c[2ln(n)]^{1/2}} \quad \text{and} \quad S_n = \frac{1}{c[2ln(n)]^{1/2}} \tag{7}$$

3.2.2 Time Series Construction

After we detect the jumps separately for overnight, intraday, and daily periods, we create different return time series for each interval. Intraday returns are simply calculated with closing and opening prices in the CRSP database. Since CRSP daily return series are adjusted for distributions, we deduce overnight returns from daily and intraday returns instead of adjusting opening prices for distributions and generating a close-to-open return time series. Specifically;

$$r_i^{ovn} = r_i - r_i^{int} \tag{8}$$

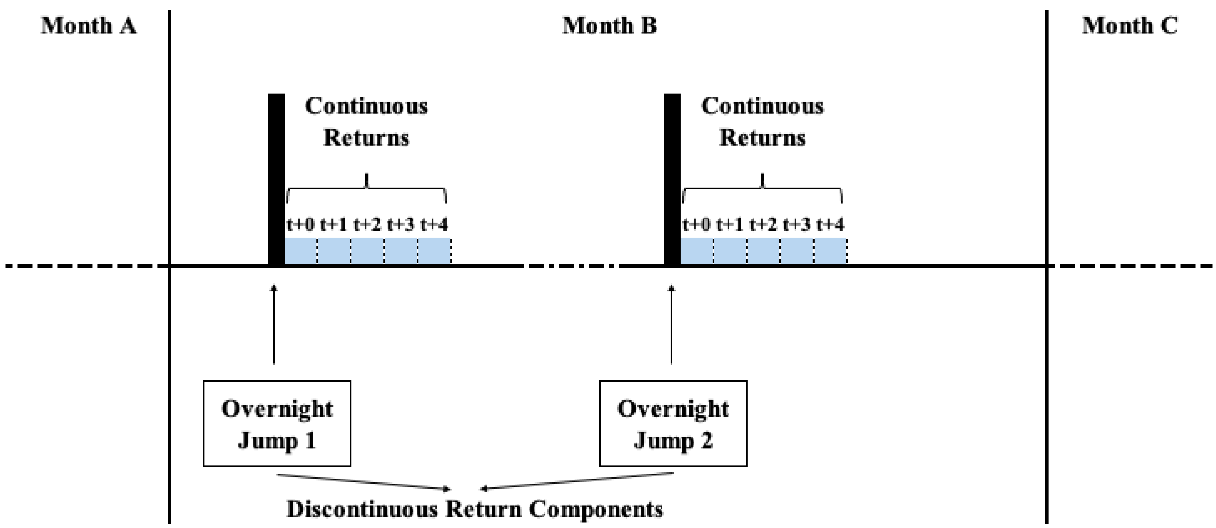
$$COR = exp(\sum_{d=1} r_{i,d}^{ovn}) - 1 \quad \text{and} \quad CIR = exp(\sum_{d=1} r_{i,d}^{int}) - 1 \quad \text{and} \quad CDR = exp(\sum_{d=1} r_{i,d}) - 1 \tag{9}$$

where $r_{i,d}^{ovn}$, $r_{i,d}^{int}$ and $r_{i,d}$ are respectively the overnight, intraday, and daily log returns of stock i on day d and COR, CIR and CDR are cumulative overnight returns, cumulative intraday returns and cumulative daily returns for a given period. To extract and cumulate the discontinuous overnight return components in a month just like Jiang and Yao (2013) do in yearly return setup for daily returns, we construct $CJR = exp(\sum_{k=1}^{N_j} r_{i,k}^{ovn}) - 1$ in which N_j stands for the counting process for overnight jumps in that month, $r_{i,k}^{ovn}$ corresponds to the overnight jump return at each jump incidence and CJR abbreviates monthly cumulative jump return.[5]

[5] Jiang and Yao (2013) disentangle continuous and discontinuous return components for each year. They first calculate cumulative jump returns and subtract it from a total cumulative return to get the continuous return component within that year.

Within non-jump days, we focus on adjacent returns immediately after these overnight jumps and construct our dependent variables by cumulating these return numbers associated with each jump. Figure 1 illustrates a specific month with two randomly arriving overnight jumps and corresponding follow-up returns. In the diagram, black episodes represent overnight discontinuities and shaded days are the subsequent returns. For this example, we calculate CJR as formulated above and $CDR_{postjump} = exp(\sum_{d=1,k=1}^{d=5,k=2} r_{i,d,k}) - 1$ for stock i where d stands for the relevant day, k stands for the jump incidence, $r_{i,1,1} = r_{i,1,1}^{int}$ and $r_{i,1,2} = r_{i,1,2}^{int}$. For each stock, we construct separate monthly time series for both negative and positive cumulative overnight jumps.

Figure 1: Discontinous Overnight Return Components and Time Series Construction



Notes: This diagram demonstrates a typical month where there are two sporadic overnight jumps. $t+0$ returns are respectively the $r_{i,1,1}^{int}$ and $r_{i,1,2}^{int}$ meaning that they are the first intraday returns following each overnight jump. The remaining $t+1$, $t+2$, $t+3$ and $t+4$ are the daily returns following the overnight jump day.

4 Empirical Findings

4.1 Jumps, Short-term Overreaction, and Return Predictability

In this subsection, we analyze how stock returns evolve after overnight price jumps. In the first place, we look at regression results for the first day just after the overnight information shocks and report the results in Table 3. Each month, we specifically run cross-sectional regressions of the stocks with overnight jump incidences. The dataset will overtly be an unbalanced panel version with irregular jump arrivals in the time dimension. The basket of stocks will also change each month depending on the availability of overnight information shocks. In the regressions, it is highly likely that the error terms will not be independent of each other since a positive/negative information shock may connote a similar case for the neighboring company. So, one needs to correct for the correlation of the errors as the standard errors will be misleading otherwise. To get the robust standard errors, we use cluster command with three digits CRSP Standard Industrial Classification Code (SICCD). We store coefficient estimates and t-stats for 342 months and their averages will be an unbiased estimator of the population counterparts. For Table 3, we run Eq. 10 starting from the most parsimonious version and expand it by adding our control variables one at a time. Basic descriptive statistics for jumps are reported in Table 1. We report descriptive statistics and correlation numbers of our variables in Table 2.[6]

We estimate:

$$\begin{aligned} CDR_{t,d+1} = \alpha + \beta_1 CJR_{t,d=0} + \beta_2 PREV_{t,d=-1} + \beta_3 IVOL_t + \beta_4 SIZE + \beta_5 BM + \\ \beta_6 LEV + \beta_7 RET_{t-1,t-5} + \beta_8 RET_{t-6,t-11} + \beta_9 AI_t + \varepsilon_t \end{aligned} \tag{10}$$

where $0 \leq d \leq 4$, $CDR_{t,d+1}$ is the monthly cumulated post-jump daily returns and $CJR_{t,d=0}$ is the cumulative overnight jump returns preceding the daily returns of our interest. For instance, $CJR_{t,d=0}$ is the cumulated overnight jump returns for random jump days of a given month t and $CDR_{t,3}$ corresponds to cumulative 3-day returns following these jumps within this month. Overnight period is regarded as $d = 0$ and the following intraday return is treated as $d = 1$. For the definition of other regressor variables, see Section 3.1. We perform separate regressions for negative and positive jump incidences.

The most striking result in Table 3 is the significance of CJR_t in all forms of regression outputs with a negative sign for both negative and positive overnight jumps. Moreover,

[6] Negative jumps are not the perfect equivalent of tail risk because of two reasons: First, even small price fluctuations outside tails may be marked as a jump during very calm periods. Second, tails also include high levels of negative returns that come in the form of volatility whereas jumps correspond to specific returns triggered by information shocks, liquidity shocks, and other imbalances related to trading. That said, jump magnitudes are generally considerable and negative jumps can be regarded as rarely and sporadically arriving proxies of tail risk. We support this argument by the high correlation of tail risk variables and $IVOL$ in Atilgan et al. (2020). Similar to that study, our CJR variable has also a high correlation with $IVOL$ for both positive and negative jumps.

Table 1:
Descriptive Statistics for Jumps

Notes: Jump Statistics are tabulated for stocks with more than 3 years of trading history in the analysis period. Each panel shows the jump statistics for each corresponding component of the day. *Int. Ret.* in the table stands for intraday returns after overnight jumps. Our analyses cover 342 months over the period July 1993 - December 2021.

Panel A: Overnight Return Jumps

	Numbers	Mean	Median	Int. Ret.<0	Int. Ret.>0	Int. Ret.=0	Opposite Sign Int. Return	Same Sign Int. Retun
Total	380,747	0.4%	-0.9%					
Negative	201,191	-6.9%	-4.8%	52,286	91,188	57,717	45%	26%
Positive	179,556	8.6%	5.2%	91,188	55,221	33,147	51%	31%

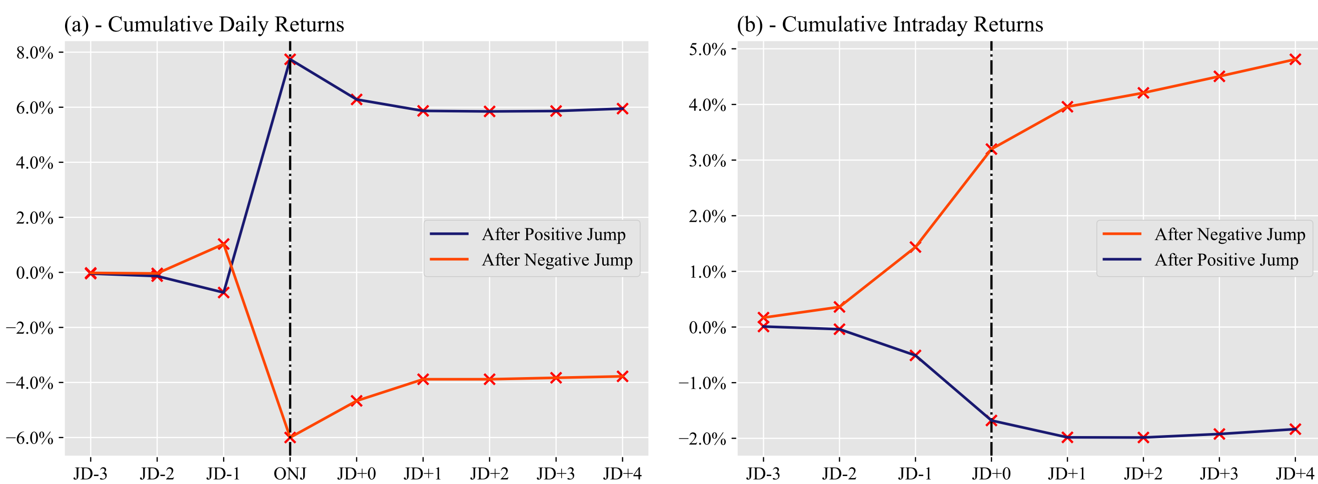
Panel B: Intraday Return Jumps

	Numbers	Mean	Median	Ovn. Ret.<0	Ovn. Ret.>0	Ovn. Ret.=0	Opposite Sign Ovn. Return	Same Sign Ovn. Return
Total	137,094	2.9%	2.6%					
Negative	62,998	-11.1%	-8.7%	26,878	34,905	1,215	55%	43%
Positive	74,096	14.9%	9.5%	41,338	31,109	1,649	56%	42%

Panel C: Daily Return Jumps

	Numbers	Mean	Median	Int. Ret.<0	Int. Ret.>0	Int. Ret.=0	Opposite Sign Int. Return	Same Sign Int. Return
Total	123,580	3.6%	3.7%					
Negative	58,108	-14.9%	-11.9%	50,948	4,168	2,992	7%	88%
Positive	65,472	20.0%	13.2%	3,967	59,262	2,243	6%	91%

Figure 2: Overreaction Path



Notes: This graph shows overreaction to overnight information shocks. The left panel plots the mean of the cumulative daily returns around negative and positive overnight price jumps whereas the right panel unravels the mean of cumulative intraday returns.

coefficients for negative and positive jump incidences are quite solid respectively around -0.80 and -0.37 through columns (3)-(9). In the largest model set-up, t-stat values are respectively 3.74 and 5.89 in absolute terms. Apparently, our CJR_t variable is orthogonal to

Table 2:
Descriptive Statistics and Correlation Matrix for Variables

This table tabulates descriptive statistics and correlations between the variables in our monthly cross-sectional regressions. We calculate the figures for each month, construct a time series and average them. CJR_t^+ and CJR_t^- are respectively the monthly cumulated positive and negative jump returns, $PREV_t$ is the monthly cumulated previous day returns before jumps, $IVOL_t$ is the idiosyncratic volatility, $SIZE$ is the log of market cap at every June, BM is the log of book-to-market ratio, LEV is the log of total assets' book value divided by the log of market equity, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are set as the lagged momentum returns split for different horizons following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), AI_t is the monthly Amihud Illiquidity measure constructed as the mean of daily figures in a month which is later multiplied by 1,000,000. Our analyses cover 342 months over the period July 1993 - December 2021. See Section 3.1 for detailed explanations of variables.

PANEL A: Descriptive Statistics

	CJR_t^+	CJR_t^-	$PREV_t$	$IVOL_t$	$SIZE$	BM	LEV	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
Mean	0.11	-0.09	-0.01	0.04	19.32	-0.65	1.07	0.05	0.07	16.74
Median	0.07	-0.06	0.00	0.03	19.17	-0.55	0.78	0.01	0.02	0.38
St. Dev.	0.16	0.08	0.08	0.04	2.01	1.07	0.89	0.39	0.44	113.59
Min	0.00	-0.67	-0.41	0.00	14.66	-5.97	0.00	-0.80	-0.80	0.00
Max	1.79	0.00	0.75	0.42	25.53	3.95	5.56	3.24	3.99	1881.77
Skew.	5.55	-3.02	2.02	4.38	0.31	-0.53	1.42	2.56	2.85	12.26
Kurto.	53.01	14.81	44.02	35.33	-0.16	4.79	2.95	23.01	25.26	189.18
25^{th} $Per.$	0.04	-0.11	-0.03	0.02	17.85	-1.18	0.41	-0.14	-0.15	0.02
75^{th} $Per.$	0.12	-0.04	0.01	0.05	20.68	-0.04	1.55	0.18	0.21	3.19

PANEL B: Correlations (Negative Jumps)

	CJR_t^-	$PREV_t$	$IVOL_t$	$SIZE$	BM	LEV	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
CJR_t^-	1.00								
$PREV_t$	-0.14	1.00							
$IVOL_t$	-0.67	0.28	1.00						
$SIZE$	0.25	-0.17	-0.35	1.00					
BM	-0.01	0.08	0.06	-0.37	1.00				
LEV	0.08	0.02	-0.06	-0.07	-0.09	1.00			
$RET_{t-1,t-5}$	0.10	-0.05	-0.13	0.03	-0.04	0.02	1.00		
$RET_{t-6,t-11}$	0.06	-0.05	-0.10	0.09	-0.16	0.00	0.00	1.00	
AI_t	-0.17	0.11	0.23	-0.24	0.12	0.02	-0.07	-0.05	1.00

PANEL C: Correlations (Positive Jumps)

	CJR_t^+	$PREV_t$	$IVOL_t$	$SIZE$	BM	LEV	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
CJR_t^+	1.00								
$PREV_t$	-0.01	1.00							
$IVOL_t$	0.71	-0.01	1.00						
$SIZE$	-0.28	0.06	-0.37	1.00					
BM	0.04	-0.03	0.06	-0.34	1.00				
LEV	-0.04	-0.01	-0.05	-0.06	-0.12	1.00			
$RET_{t-1,t-5}$	-0.11	0.03	-0.14	0.05	-0.05	0.00	1.00		
$RET_{t-6,t-11}$	-0.09	0.02	-0.11	0.10	-0.16	-0.01	0.02	1.00	
AI_t	0.14	-0.08	0.21	-0.23	0.11	0.02	-0.07	-0.05	1.00

all control variables and these findings all together mean that cumulative jump returns have a distinctive and significant predictive power for the follow-up equity returns. Among other control variables, only $SIZE$ and $IVOL_t$ are statistically significant in explaining variations in cumulated returns within this short-event window.

Figure 2 demonstrates three important empirical facts to us. First, it visually shows the

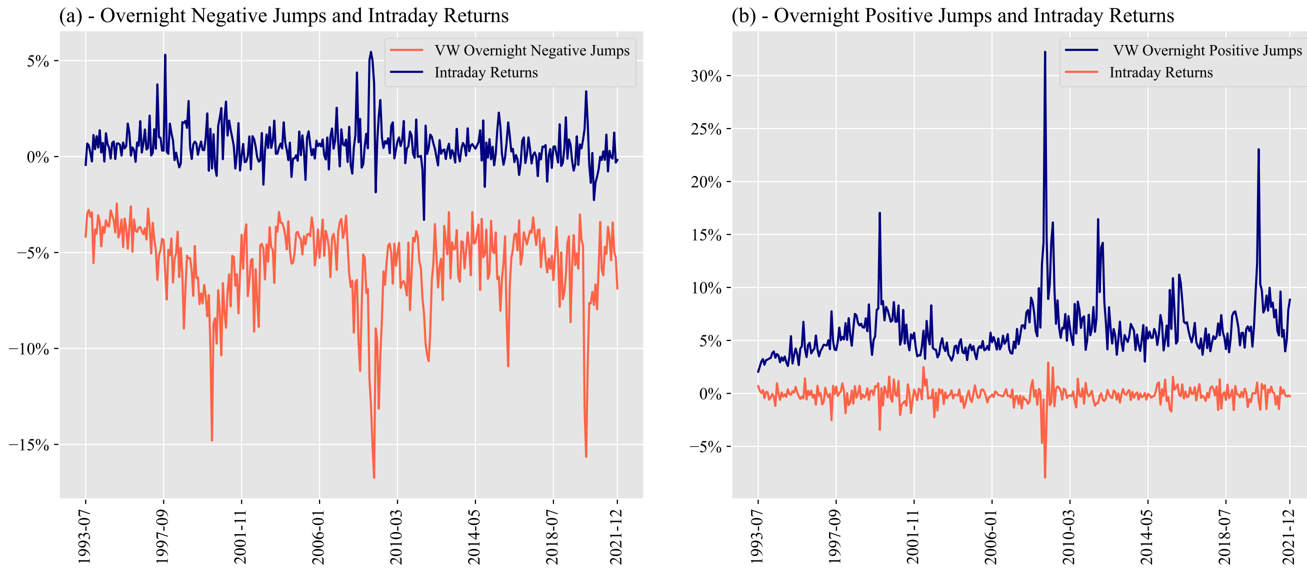
Table 3:
Cross-Sectional Regressions for Return Predictability

To disentangle the discontinuous overnight components of monthly returns, we calculate cumulative overnight positive and negative jump returns. On a monthly scale, we also calculate cumulative post-jump intraday returns for the first day as shown in Section 3.2.2 and construct our dependent variable IR_t. Then, we run monthly cross-sectional regressions and save the coefficients and t-stats. To correct the correlation of the errors and get robust standard errors, we use cluster command with three digits CRSP Standard Industrial Classification Code (SICCD). From columns (2) to (9), we add each firm-specific control variable one at a time. This table reports results only for the first day after jumps and results of the other days are available upon request. Table populates averaged monthly coefficient estimates and t-statistics from the monthly regressions. CJR_t^+ and CJR_t^- are respectively the monthly cumulated positive and negative jump returns, $PREV_t$ is the monthly cumulated previous day returns before jumps, $IVOL_t$ is the idiosyncratic volatility, $SIZE$ is the log of market cap at every June, BM is the log of book-to-market ratio, LEV is the log of total assets' book value divided by the log of market equity, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are set as the lagged momentum returns split for different horizons following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), AI_t is the monthly Amihud Illiquidity measure constructed as the mean of daily figures in a month which is later multiplied by 1,000,000. Estimated regression coefficients for BM, LEV, $RET_{t-1,t-5}$, $RET_{t-6,t-11}$ and AI_t are multiplied by 100. Our analyses cover 342 months over the period July 1993 - December 2021. See Section 3.1 for the detailed explanations of variables.

PANEL A: Negative Jumps									
Dep. Variable: (IR_t)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
CJR_t^-	-0.43	-0.44	-0.79	-0.79	-0.79	-0.79	-0.79	-0.80	-0.79
	(-1.81)	(-1.84)	(-3.58)	(-3.66)	(-3.68)	(-3.68)	(-3.69)	(-3.7)	(-3.74)
$PREV_t$		-0.04	0.07	0.05	0.05	0.05	0.05	0.05	0.04
		(-0.33)	(0.77)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.6)
$IVOL_t$			-1.58	-1.80	-1.80	-1.80	-1.84	-1.85	-1.87
			(-3.04)	(-3.38)	(-3.39)	(-3.39)	(-3.44)	(-3.47)	(-3.44)
$SIZE_t$				-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
				(-3.44)	(-3.18)	(-3.17)	(-3.16)	(-3.15)	(-3.09)
BM_t					0.32	0.33	0.28	0.23	0.21
					(0.03)	(0.01)	(-0.01)	(-0.1)	(-0.13)
LEV_t						0.03	0.02	0.02	0.00
						(-0.03)	(-0.02)	(-0.02)	(-0.04)
$RET_{t-1,t-5}$							-1.77	-1.80	-1.76
							(-0.48)	(-0.49)	(-0.48)
$RET_{t-6,t-11}$								-0.16	-0.22
								(-0.48)	(-0.48)
AI_t									0.02
									(0.2)
Intercept	-0.02	-0.03	0.00	0.18	0.16	0.16	0.16	0.17	0.17
	(0.04)	(-0.01)	(1.77)	(3.54)	(3.34)	(3.27)	(3.27)	(3.27)	(3.21)
$Adj.R^2$	0.08	0.10	0.20	0.23	0.24	0.24	0.24	0.24	0.25

PANEL B: Positive Jumps									
Dep. Variable: (IR_t)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
CJR_t^+	-0.11	-0.12	-0.37	-0.37	-0.37	-0.37	-0.37	-0.37	-0.37
	(-2.46)	(-2.56)	(-5.53)	(-5.73)	(-5.75)	(-5.77)	(-5.81)	(-5.81)	(-5.89)
$PREV_t$		0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.01
		(0.52)	(0.37)	(0.2)	(0.21)	(0.21)	(0.21)	(0.21)	(0.19)
$IVOL_t$			1.31	1.48	1.49	1.50	1.53	1.54	1.55
			(4.33)	(4.95)	(4.98)	(5.02)	(5.12)	(5.16)	(5.18)
$SIZE_t$				0.01	0.01	0.01	0.01	0.01	0.01
				(4.73)	(4.58)	(4.64)	(4.67)	(4.65)	(4.63)
BM_t					0.15	0.17	0.21	0.27	0.28
					(0.51)	(0.58)	(0.65)	(0.77)	(0.8)
LEV_t						0.14	0.14	0.15	0.15
						(0.47)	(0.47)	(0.48)	(0.49)
$RET_{t-1,t-5}$							1.57	1.59	1.56
							(1.11)	(1.13)	(1.11)
$RET_{t-6,t-11}$								0.94	0.93
								(0.81)	(0.81)
AI_t									0.01
									(0.05)
Intercept	0.00	0.00	-0.03	-0.20	-0.21	-0.21	-0.21	-0.21	-0.21
	(-0.28)	(-0.26)	(-3.54)	(-4.99)	(-4.91)	(-4.92)	(-4.96)	(-4.95)	(-4.94)
$Adj.R^2$	0.07	0.10	0.30	0.34	0.34	0.34	0.35	0.35	0.36

Figure 3: Overnight Jumps and Intraday Returns

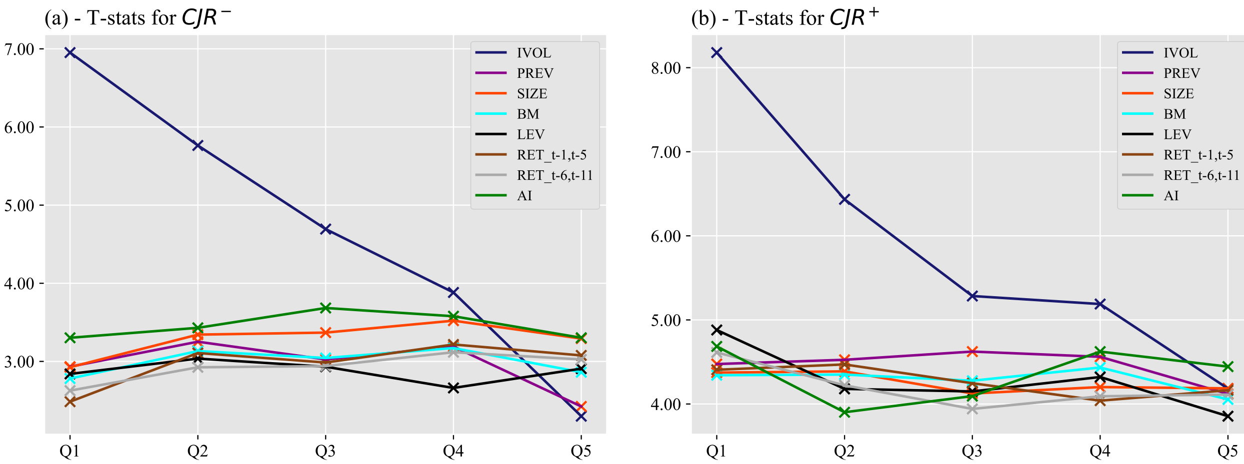


Notes: This graph shows value-weighted overnight jump returns and their value-weighted counterpart in the following intraday section.

overreaction during overnight negative and positive jumps by plotting the mean of follow-up cumulative daily returns in the left panel. This trend can also be visually inspected via Figure 3 as well. Second, the intraday portion of cumulative returns is more powerful after negative jumps as plotted in the right panel of Figure 2. A closer look into Figure 3 also reveals similar market behaviour: post-jump intraday returns wander mostly above zero after negative overnight jumps and below zero after positive overnight shocks though this is less powerful when compared with the negative case. This is in line with the asymmetric intraday reaction depicted in subplot 2b of Figure 2. Third, overnight jumps are preceded by an opposite sign average daily return. Actually, we can see that the daily cumulative return is 1.03% on day $JD-1$ in the case of negative jumps and the trend is upward just like the post-jump period, and -0.7% in the case of positive jumps and the trend is downward just like the post-jump period. To control for this previous day's information, we introduce $PREV_{t,d=-1}$ and populated results in Table 3 and Table 5 show that the previous day's information does not have statistically significant explanatory power.

Our regressions also show that book-to-market ratios (BM), leverage (LEV), momentum ($RET_{t-1,t-5}$ and $RET_{t-6,t-11}$), firm-specific illiquidity (AI_t) do not have a statistically significant effect on the return behaviors around these short-term overreaction episodes. These

Figure 4: Significance of CJR in Quintile Portfolios



Notes: This graph shows the robust t-stats values for CJR obtained in different regressions. At each month, we sort overnight jump stocks in ascending order based on the values of control variables and form quintile portfolios. Then, we run monthly cross-sectional regressions and save the coefficients and t-stats. To correct the correlation of the errors and get robust standard errors, we use cluster command with three digits CRSP Standard Industrial Classification Code (SICCD). With 8 control variables, we employ cross-sectional regressions for 40 different portfolio formation rules. CJR^{-} and CJR^{+} are respectively the monthly cumulated negative and positive jump returns, $PREV$ is the cumulated previous day return to control for the information before the overnight period, $IVOL$ is the idiosyncratic volatility, $SIZE$ is the log of market cap at every June, BM is the log of book-to-market ratio, LEV is the log of total assets' book value divided by the log of market equity, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are set as the lagged momentum returns split for different horizons following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), AI is the monthly Amihud Illiquidity measure constructed as the mean of daily figures in a month which is later multiplied by 1,000,000. See Section 3.1 for detailed explanations of variables.

firm-specific factors (which are regarded as proxies for different risks) lose their predictive power during these times. Only $SIZE$ and $IVOL_t$ remain as firm-specific risk factors with significant coefficients. These findings conform to the gist of Kamara et al. (2016) as some factors may not be priced for certain horizons whereas some gain predictive power in the same time span. On the other hand, CJR_t is statistically significant in all regression results as a factor of information shocks (see Table 3 and Table 5). To check the significance of CJR in different stock groups, we repeat our analysis by forming quintile portfolios based on each control variable. At each month, we sort jump stocks in ascending order according to the values of control variables, split them into quintiles, and run cross-sectional regressions.

Hence, we employ this set-up for 40 different portfolio formation rules and save the t-stat values. Results are depicted in Figure 4. It is blatant that t-stat values for CJR hover around certain levels regardless of the quintile portfolios for all control variables, but for $IVOL$. For $IVOL$, the significance of CJR visibly boosts towards the quintile with the lowest idiosyncratic volatility values. Table 4 reports different regression outputs for different quintiles of $IVOL$. It is clear that CJR progressively becomes more significant as the stocks become less volatile.[7] All in all, our findings show that cross-sectional return predictability around these short-event windows (the very few days after overnight jumps) is explained partly by firm characteristics and partly by our cumulative jump return factor that proxies information shocks.

Some control variables deserve deeper analysis. The coefficients of $IVOL_t$ are negative for all days in Panel A of Table 5 and statistically significant with alternating significance levels at all days. Stocks with higher idiosyncratic volatility have lower cumulative daily returns after negative overnight jumps. This is compatible with the literature on idiosyncratic volatility puzzle due to Ang et al. (2006). The coefficient of $SIZE$ is also in line with the extant literature and it is statistically significant for all days. However, in explaining the cumulative returns after positive overnight jumps, coefficient signs for $SIZE$ and $IVOL_t$ switch. At first glance, it is tempting to assert that the idiosyncratic volatility puzzle is solved for positive jump stocks at this short return window due to the positive sign for $IVOL_t$ because it implies that stocks with higher idiosyncratic volatility have higher post-positive-jump returns. Actually, dependent variables in Panel B of Table 5 are not necessarily composed of negative returns. However, the average reaction after positive overnight jumps is negative as shown in Figure 2. In this figure, we show the mean of all cumulative returns before and after negative and positive overnight jumps. The left panel in Figure 2 shows cumulative daily returns whereas the right panel is generated with cumulative returns of intraday components.[8] Hence, we interpret the positive sign of $IVOL_t$ as again compatible with literature as opposed to the disappearance of the idiosyncratic volatility puzzle. It can also be interpreted as stocks with higher $IVOL_t$ numbers perform better when cumulative returns are negative on average. We can make a similar interpretation for $SIZE$ as well.

[7] Regression results based on other sorted control variables are not reported for the sake of brevity but they are available upon request.

[8] Jump day return in the right panel of Figure 2 is the intraday return coinciding with the jump day.

Table 4:
Regressions for Different Quintiles of IVOL

This table is complementary to Figure 4 and shows the regression outputs for portfolios formed according to different $IVOL$ quintiles. At each month, we sort overnight jump stocks in ascending order based on the $IVOL$ numbers and form quintile portfolios. Then, we run monthly cross-sectional regressions and save the coefficients and t-stats. To correct the correlation of the errors and get robust standard errors, we use cluster command with three digits CRSP Standard Industrial Classification Code (SICCD). Table populates averaged monthly coefficient estimates and t-statistics from the monthly regressions. CJR_t^+ and CJR_t^- are respectively the monthly cumulated positive and negative jump returns, $PREV_t$ is the monthly cumulated previous day returns before jumps, $IVOL_t$ is the idiosyncratic volatility, $SIZE$ is the log of market cap at every June, BM is the log of book-to-market ratio, LEV is the log of total assets' book value divided by the log of market equity, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are set as the lagged momentum returns split for different horizons following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), AI_t is the monthly Amihud Illiquidity measure constructed as the mean of daily figures in a month which is later multiplied by 1,000,000. Estimated regression coefficients for BM, LEV, $RET_{t-1,t-5}$, $RET_{t-6,t-11}$ and AI_t are multiplied by 100. Our analyses cover 342 months over the period July 1993 - December 2021. See Section 3.1 for the detailed explanations of variables.

Negative Overnight Jumps

	Int.	CJR_t^-	$PREV_t$	$IVOL_t$	$SIZE_t$	BM_t	LEV_t	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t	$Adj.R^2$
Q1	0.04	-0.88	-0.03	-1.59	0.00	-0.04	-0.03	-0.40	0.24	-0.06	0.48
	(1.09)	(-6.95)	(-0.22)	(-1.92)	(-1.02)	(-0.15)	(-0.13)	(-0.12)	(0.11)	(-1.28)	
Q2	0.11	-0.85	-0.03	-2.16	0.00	-0.10	-0.09	-0.21	-0.13	0.03	0.41
	(1.75)	(-5.76)	(-0.18)	(-1.06)	(-1.91)	(-0.25)	(-0.27)	(-0.12)	(-0.02)	(-1.14)	
Q3	0.21	-0.76	-0.02	-2.26	-0.01	-0.18	-0.25	-0.73	-0.06	0.59	0.35
	(2.23)	(-4.69)	(-0.17)	(-1.09)	(-2.53)	(-0.46)	(-0.36)	(-0.25)	(-0.03)	(-1.09)	
Q4	0.33	-1.04	-0.02	-2.78	-0.02	0.18	-0.37	-0.13	2.28	0.84	0.32
	(2.56)	(-3.88)	(0.02)	(-1.44)	(-2.73)	(-0.38)	(-0.11)	(-0.19)	(-0.12)	(-0.79)	
Q5	0.44	-0.67	0.03	-1.47	-0.02	0.04	0.27	-3.03	-2.10	0.25	0.24
	(2.1)	(-2.3)	(0.24)	(-1.71)	(-2.18)	(-0.13)	(0.14)	(-0.5)	(-0.43)	(0.21)	

Positive Overnight Jumps

	Int.	CJR_t^+	$PREV_t$	$IVOL_t$	$SIZE_t$	BM_t	LEV_t	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t	$Adj.R^2$
Q1	-0.05	-0.69	0.01	1.47	0.00	0.05	0.06	0.11	0.16	0.08	0.42
	(-1.58)	(-8.18)	(0.1)	(2.04)	(1.43)	(0.18)	(0.21)	(0.11)	(0.17)	(0.81)	
Q2	-0.12	-0.61	0.01	1.81	0.01	0.13	0.15	0.22	0.22	-0.42	0.37
	(-2.1)	(-6.43)	(0.14)	(1.15)	(2.33)	(0.39)	(0.43)	(0.09)	(0.13)	(0.9)	
Q3	-0.20	-0.54	0.02	1.99	0.01	0.26	0.19	0.76	0.41	-0.19	0.35
	(-2.58)	(-5.28)	(0.24)	(1.2)	(2.88)	(0.53)	(0.5)	(0.34)	(0.21)	(0.6)	
Q4	-0.29	-0.48	0.02	1.81	0.01	0.45	0.18	1.30	0.57	-0.09	0.35
	(-2.89)	(-5.19)	(0.18)	(1.37)	(3.2)	(0.73)	(0.34)	(0.54)	(0.21)	(0.75)	
Q5	-0.39	-0.32	0.01	1.62	0.02	0.26	-0.34	2.88	1.34	-0.34	0.38
	(-2.59)	(-4.18)	(0.12)	(4.11)	(2.35)	(0.33)	(-0.19)	(0.87)	(0.52)	(-0.15)	

4.2 Costly Arbitrage as a Source of Reversal Degree

Inspired by the work of Atilgan et al. (2020), we are analyzing how costly arbitrage conditions affect the overreaction pattern for stocks with different characteristics[9]. Atilgan et al. (2020) report that stocks with higher left-tail risk have anomalously lower future returns since investors underreact to bad news and do not properly process the embedded information. They continue demanding those stocks and thereby create overpricing. The gist of our paper

[9]We are grateful to Turan Bali from McDonough School of Business at Georgetown University for catching our attention to this issue and for his insightful comments.

Table 5:
Daily Return Predictability After Overnight Jump

To disentangle the discontinuous overnight components of monthly returns, we calculate cumulative overnight positive and negative jump returns. On a monthly scale, we also calculate cumulative post-jump returns up to five days as shown in Section 3.2.2, and construct our dependent variables. Then, we run monthly cross-sectional regressions and save the coefficients and t-stats. To correct the correlation of the errors and get robust standard errors, we use cluster command with three digits CRSP Standard Industrial Classification Code (SICCD). The dependent variable $1D_t$ is the intraday return just after the overnight jump. For the other days, the dependent variable represents cumulative return up to that day after jump incidence. Table populates averaged monthly coefficient estimates and t-statistics from the monthly regressions. CJR_t^+ and CJR_t^- are respectively the monthly cumulated positive and negative jump returns, $PREV_t$ is the monthly cumulated previous day returns before jumps, $IVOL_t$ is the idiosyncratic volatility, $SIZE$ is the log of market cap at every June, BM is the log of book-to-market ratio, LEV is the log of total assets' book value divided by the log of market equity, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are set as the lagged momentum returns split for different horizons following Grinblatt and Moskowitz (2004) and Jiang and Zhu (2017), AI_t is the monthly Amihud Illiquidity measure constructed as the mean of daily figures in a month which is later multiplied by 1,000,000. Estimated regression coefficients for BM, LEV, $RET_{t-1,t-5}$, $RET_{t-6,t-11}$ and AI_t are multiplied by 100. Our analyses cover 342 months over the period July 1993 - December 2021. See Section 3.1 for the detailed explanations of variables.

PANEL A: Negative Jumps										
Dep. Variable	$1D_t$		$2D_t$		$3D_t$		$4D_t$		$5D_t$	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	0.17	(3.21)	0.17	(2.79)	0.17	(2.56)	0.16	(2.29)	0.15	(2.06)
CJR_t^-	-0.79	(-3.74)	-0.82	(-3.4)	-0.78	(-2.98)	-0.71	(-2.63)	-0.69	(-2.33)
$PREV_t$	0.04	(0.6)	0.07	(0.67)	0.02	(0.27)	0.02	(0.29)	0.02	(0.19)
$IVOL_t$	-1.87	(-3.44)	-1.70	(-2.64)	-1.58	(-2.35)	-1.38	(-2)	-1.25	(-1.74)
$SIZE_t$	-0.01	(-3.09)	-0.01	(-2.77)	-0.01	(-2.53)	-0.01	(-2.27)	-0.01	(-2.03)
BM_t	0.21	(-0.13)	0.39	(0.19)	0.46	(0.23)	0.43	(0.24)	0.50	(0.28)
LEV_t	0.00	(-0.04)	0.19	(0.26)	0.21	(0.24)	0.18	(0.23)	0.23	(0.24)
$RET_{t-1,t-5}$	-1.76	(-0.48)	-1.33	(-0.24)	-1.51	(-0.3)	-1.30	(-0.28)	-1.37	(-0.32)
$RET_{t-6,t-11}$	-0.22	(-0.48)	0.09	(-0.21)	0.06	(-0.19)	0.13	(-0.15)	0.20	(-0.1)
AI_t	0.02	(0.2)	0.04	(1.8)	0.05	(1.78)	0.03	(1.53)	0.03	(1.39)
$Adj.R^2$	0.25		0.28		0.24		0.22		0.20	

PANEL B: Positive Jumps										
Dep. Variable	$1D_t$		$2D_t$		$3D_t$		$4D_t$		$5D_t$	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	-0.21	(-4.94)	-0.24	(-4.25)	-0.25	(-3.85)	-0.25	(-3.56)	-0.25	(-3.33)
CJR_t^+	-0.37	(-5.89)	-0.35	(-4.55)	-0.35	(-4.09)	-0.34	(-3.65)	-0.33	(-3.33)
$PREV_t$	0.01	(0.19)	0.04	(0.07)	0.02	(-0.09)	0.03	(-0.06)	0.04	(-0.02)
$IVOL_t$	1.55	(5.18)	1.47	(3.76)	1.47	(3.38)	1.47	(3.19)	1.46	(3)
$SIZE_t$	0.01	(4.63)	0.01	(4.07)	0.01	(3.69)	0.01	(3.41)	0.01	(3.2)
BM_t	0.28	(0.8)	0.25	(0.51)	0.24	(0.48)	0.27	(0.46)	0.28	(0.49)
LEV_t	0.15	(0.49)	0.06	(0.13)	0.10	(0.2)	0.11	(0.21)	0.07	(0.18)
$RET_{t-1,t-5}$	1.56	(1.11)	1.69	(0.89)	1.71	(0.83)	1.75	(0.75)	1.79	(0.71)
$RET_{t-6,t-11}$	0.93	(0.81)	0.93	(0.61)	0.97	(0.59)	0.92	(0.54)	0.88	(0.51)
AI_t	0.01	(0.05)	0.00	(-0.61)	0.00	(-0.75)	0.00	(-0.63)	0.00	(-0.55)
$Adj.R^2$	0.36		0.27		0.24		0.21		0.19	

is however the investor overreaction to negative and positive overnight information shocks which is later reversed to some extent. In other words, our study is different than theirs in certain aspects. First, they are looking at one-month ahead return predictability whereas our focus is the short-term return predictability up to five days which is grounded only on overnight information shocks. Second, our study encompasses both positive and negative extreme returns marked as jumps whereas Atilgan et al. (2020) focus only on the extreme losses in the left tail. Tail risks are generally estimated with a threshold approach through Value-at-Risk (VaR) and Expected Shortfall (ES) metrics. It is crucial to state that these extreme losses below a certain cut-off point are comprised of returns originated by both volatility and jump. Nonetheless, our study distinctively focuses only on returns in the form of price discontinuities and these jump returns need not be below a certain cutoff level; the essence of the VaR and ES approaches.

The level of correction in the mispricing is not homogeneous among stocks with different characteristics which are essential in impelling arbitrageurs to step in. Bunch of literature documents that there are *limits to arbitrage* (Shleifer and Vishny (1997), Hirshleifer (2001) and Kyle and Xiong (2001)) among many others) and arbitrage practices are not perfectly mechanical and not riskless. Willingness for price correction decays even further when the level of mispricing is intense. As also pointed out by Atilgan et al. (2020) and relevant literature, idiosyncratic risk is regarded as one of the most crucial arbitrage costs especially when it is combined with extreme noise trading. In Table 6 and Table 7, we delve into price reversals and their association with the stocks' idiosyncratic risks. In that regard, we expect the fraction of jump returns that is reversed to be lower for stocks with higher levels of idiosyncratic volatility. We also repeat our analysis for different levels of AI figures.

We report results for the first three days after negative and positive jump incidences. Stocks are primarily sorted according to their $IVOL$ levels as it is a powerful indicator for arbitrageurs whether to engage in price correction activity or not. At each month, stocks are sorted in ascending order according to their monthly $IVOL$ numbers. We split the sorted stock list into quintiles and analyze their jump and reversal patterns thoroughly. $Q5$ contains the riskiest and the most illiquid stocks whereas $Q1$ encloses stocks with the lowest idiosyncratic volatility and illiquidity levels.

The fraction of jump that is reversed is shown in column $Reversal/Jump$ with a positive sign. Panel A both in Table 6 and Table 7 tabulates results for quintile portfolios constructed according to ascending $IVOL$ levels and Panel B shows the results for AI figures. Findings in Panel A explicitly reveal that jump magnitudes for $Q5$ stocks are quite large and significantly different than those of stocks in $Q1$. That is in line with our expectations before the analysis.

Strikingly, 51% of the negative overnight jump is reversed for $Q1$ stocks in the intraday period right after the overnight jump whereas this fraction is only 8% for $Q5$ stocks. At the end of the second and third days after the jump, the reversal fraction is respectively 58% and 59% for $Q1$ stocks although the numbers are 19% for $Q5$ in those days. For positive overnight jumps, we show that 40% of the jump is reversed in the first day after the overnight jump for $Q1$ stocks whereas this fraction is only 3% for stocks with the highest idiosyncratic volatility numbers. The reversal fraction is 40% and 38% after two and three days following the jump for $Q1$ stocks while the fractions for $Q5$ stocks are 6% and 7% respectively. We also document that these reversal fractions for negative and positive jump incidences are significantly different from each other. The surging significance of CJR across decreasing values of $IVOL$ as shown in Figure 4 forms a complementary argument to the reasoning raised here.

We replicate our analysis by sorting stocks according to their AI figures on the jump day within each month and document our findings for negative and positive overnight jumps in Panel B of Table 6 and Table 7. The highest fraction of reversal for stock-specific illiquidity is similarly observed in stocks grouped under the $Q1$ quintile although we don't see a clear directional pattern across quintiles for increasing illiquidity levels. For negative jumps, 38% of jump magnitude is reversed on jump day for $Q1$ stocks whereas this is 30% for the most illiquid group. One can discern that jump magnitudes in quintile portfolios are remarkably close to each other when compared to the IVOL-sorting scheme. On the other hand, jump sizes for each quintile in IVOL-sorting practice are perfectly in line with the order of each portfolio with a very blatant directional pattern. For positive overnight jumps, the reversed jump fraction is again the highest in the most liquid quintile with 35% on jump day whereas this is 15% for the $Q5$ portfolio group. In the following two days, the reversed negative jump fractions become 56% and 57% in the $Q5$ portfolio although it is 34% and 35% for the most liquid stocks. After the positive jumps, $Q1$ stocks' reversal degree is around 30% whereas this is 27% for the most illiquid stocks.

With these results at hand, investors do consider the idiosyncratic volatility levels as a critical cost in their trading practices and refrain from exploiting the overreaction pattern for highly volatile stocks. If Amihud illiquidity is taken as the decision criterion, we still get the same reaction on the first day for negative and positive overnight jumps. That

Table 6:
Costly Arbitrage and Reversals - Negative Overnight Jumps

Below table shows how costly arbitrage hinders the correction in mispricing fueled by the investor overreaction to overnight information shocks. *Reversal* is the cumulative returns until each specified day after the jump incidence. *Reversal/Jump* is the fraction of jumps that is cumulatively reversed in respective days. At each month, we separately sort stocks in ascending order according to their Idiosyncratic Volatility ($IVOL$) levels during that month and their Amihud Illiquidity (AI) figures on jump day and split the sorted stocks in quintiles. *Quintile 1* is for the stocks with lowest AI and $IVOL$ figures. For each month, we take the average of cumulative reversal returns within each quintile and construct different time series for them. Tabulated numbers are the time-series averages for each day after overnight negative jump incidence. $Q5 - Q1$ stands for the mean differences for each column variable with t-statistics values below in parenthesis. Our analyses cover 342 months over the period July 1993 - December 2021.

NEGATIVE JUMPS

Panel A:Stocks are Sorted According to Idiosyncratic Volatility Figures

	JumpDay			**Jump Day+1**			**Jump Day+2**		
	Reversal	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**
Quintile 1	1.7%	-3.2%	**0.51**	1.9%	-3.2%	**0.58**	1.9%	-3.2%	**0.59**
Quintile 2	1.9%	-4.7%	**0.40**	2.2%	-4.7%	**0.47**	2.2%	-4.7%	**0.47**
Quintile 3	1.9%	-6.1%	**0.30**	2.3%	-6.1%	**0.37**	2.2%	-6.1%	**0.37**
Quintile 4	2.2%	-8.4%	**0.22**	2.7%	-8.4%	**0.29**	2.6%	-8.4%	**0.29**
Quintile 5	1.2%	-15.1%	**0.08**	2.7%	-15.1%	**0.19**	2.7%	-15.1%	**0.19**
Q1-Q5	0.5%	11.9%	**0.43**	-0.8%	11.9%	**0.39**	-0.8%	11.9%	**0.39**
	(1.77)	(53.02)	**(22.47)**	(-2.37)	(53.02)	**(16.61)**	(-2.23)	(53.02)	**(15.79)**

Panel B: Stocks are Sorted According to Amihud Illiquidity Figures

	Jump Day			**Jump Day+1**			**Jump Day+2**		
	Reversal	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**
Quintile 1	2.1%	-5.9%	**0.38**	2.0%	-5.9%	**0.34**	2.0%	-5.9%	**0.35**
Quintile 2	0.9%	-7.2%	**0.14**	1.0%	-7.2%	**0.15**	1.0%	-7.2%	**0.15**
Quintile 3	1.3%	-7.5%	**0.19**	1.3%	-7.5%	**0.22**	1.3%	-7.5%	**0.22**
Quintile 4	1.9%	-8.1%	**0.23**	2.3%	-8.1%	**0.32**	2.2%	-8.1%	**0.31**
Quintile 5	2.8%	-8.6%	**0.30**	5.2%	-8.6%	**0.56**	5.3%	-8.6%	**0.57**
Q1-Q5	-0.7%	2.7%	**0.08**	-3.2%	2.7%	**-0.22**	-3.3%	2.7%	**-0.22**
	(-1.07)	(15.21)	**(2.05)**	(-5.13)	(15.21)	**(-5.6)**	(-5.38)	(15.21)	**(-5.76)**

said, Amihud Illiquidity figures in negative overnight jumps do not produce the same result in the following days. Taken together, we conjecture that investors want to be confident about the degree of price fluctuations and want to be hurt less when they intend to unwind their positions. Hence, our study sheds light on investor overreaction and the resultant mispricing. Arbitrageurs are less willing to step in and correct the mispricing for stocks that are costlier to arbitrage and the reversal is more pronounced for jump stocks when the associated arbitrage cost, proxied by idiosyncratic volatility and illiquidity levels, is lower.

Another finding that conforms to the behavioral dimensions of sharp price movements is the overall levels of price reversals after negative and positive overnight information shocks. It is obvious from Table 6 and Table 7 that the degree of reversal is notably higher in all quintiles on all days after negative jumps and that supports the premise of asymmetric reaction to negative and positive information shocks and aligns with investors' psychological inclination to be more sensitive to negative shocks. To put it differently, investors are overreacting more to unexpected negative news flows than they do to positive information shocks.

Table 7:
Costly Arbitrage and Reversals - Positive Overnight Jumps

Below table shows how costly arbitrage hinders the correction in mispricing fueled by the investor overreaction to overnight information shocks. *Reversal* is the cumulative returns until each specified day after the jump incidence. *Reversal/Jump* is the fraction of jumps that is cumulatively reversed in respective days. At each month, we separately sort stocks in ascending order according to their Idiosyncratic Volatility ($IVOL$) levels during that month and their Amihud Illiquidity (AI) figures on jump day and split the sorted stocks in quintiles. *Quintile 1* is for the stocks with lowest AI and $IVOL$ figures. For each month, we take the average of cumulative reversal returns within each quintile and construct different time series for them. Tabulated numbers are the time-series averages for each day after overnight negative jump incidence. $Q5 - Q1$ stands for the mean differences for each column variable with t-statistics values below in parenthesis. Our analyses cover 342 months over the period July 1993 - December 2021.

POSITIVE JUMPS

Panel A: Stocks are Sorted According to Idiosyncratic Volatility Figures

	Jump Day			**Jump Day+1**			**Jump Day+2**		
	Reversal	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**
Quintile 1	-1.4%	3.4%	**0.40**	-1.5%	3.4%	**0.40**	-1.4%	3.4%	**0.38**
Quintile 2	-1.5%	5.2%	**0.27**	-1.6%	5.2%	**0.29**	-1.6%	5.2%	**0.28**
Quintile 3	-1.5%	7.0%	**0.20**	-1.6%	7.0%	**0.23**	-1.6%	7.0%	**0.22**
Quintile 4	-1.6%	10.1%	**0.15**	-1.9%	10.1%	**0.18**	-1.9%	10.1%	**0.17**
Quintile 5	-0.4%	22.1%	**0.03**	-1.1%	22.1%	**0.06**	-1.2%	22.1%	**0.07**
Q1-Q5	-1.0%	-18.7%	**0.37**	-0.3%	-18.7%	**0.34**	-0.2%	-18.7%	**0.32**
	(-6.03)	(-32.05)	**(36.36)**	(-1.71)	(-32.05)	**(26.51)**	(-0.89)	(-32.05)	**(21.11)**

Panel B: Stocks are Sorted According to Amihud Illiquidity Figures

	Jump Day			**Jump Day+1**			**Jump Day+2**		
	Reversal	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**	**Reversal**	**Jump**	**Reversal/Jump**
Quintile 1	-2.2%	6.9%	**0.35**	-1.9%	6.9%	**0.30**	-1.8%	6.9%	**0.29**
Quintile 2	-0.6%	9.3%	**0.05**	-0.6%	9.3%	**0.04**	-0.7%	9.3%	**0.04**
Quintile 3	-0.8%	10.3%	**0.08**	-0.9%	10.3%	**0.08**	-0.8%	10.3%	**0.07**
Quintile 4	-1.3%	10.4%	**0.12**	-1.4%	10.4%	**0.15**	-1.5%	10.4%	**0.14**
Quintile 5	-1.6%	10.9%	**0.15**	-2.9%	10.9%	**0.27**	-3.0%	10.9%	**0.27**
Q1-Q5	-0.6%	-4.1%	**0.20**	1.0%	-4.1%	**0.03**	1.1%	-4.1%	**0.02**
	(-5.09)	(-14.09)	**(15.04)**	(7.57)	(-14.09)	**(2.38)**	(7.19)	-14.09	**1.29**

4.3 Trading Strategies

Investors are implementing dynamic trading strategies with various expectations for the future. In our case, we check if a trading strategy based on jump classification can generate risk-adjusted returns or end up in losses. We do our analysis for all overnight jump stocks in a given month and derive the results with an iterative process. At the end of each month, we first calculate the cumulative overnight jump returns of stocks and sort them in ascending order according to these returns. Sorted stocks are split into deciles with $D1$ having the lowest return and $D10$ with the highest return. Afterward, we calculate value-weighted portfolio returns for one-month investment horizon distinctively for each decile.

Our main purpose is to check both contrarian and relative strength trading strategies for these jump stocks. Although our analysis showed a short-term overreaction pattern around jump days, we wonder if the returns -after some time- show a drift pattern as opposed to a reversal. As tabulated in Table 8, a contrarian trading strategy for the stocks with the lowest negative overnight jump returns incurs -0.3% abnormal return though the Newey-West t-statistics is -1.14. However, a contrarian strategy for positive overnight jump stocks in the last decile results in a -0.7% abnormal return with a significant Newey-West t-statistics of -2.54. A zero-cost trading strategy that longs $D1$ and shorts $D10$ portfolios ends up -0.6% of abnormal return with a significant Newey-West t-statistics of -2.03. This combined contrarian trading strategy incurs 0.8% abnormal loss with again a significant t-statistics of -2.1 if we instead use $D1$ and $D5$ portfolios. These results cumulatively tell us that stocks with prior positive overnight jump returns in a month continue to perform well -at least do not reverse- when the next month's portfolio returns are considered. The overreaction pattern in the wake of overnight information shocks morphs into drifting returns when the next-month investment portfolios are considered.

4.4 "Tug of War" Under Overnight Jumps

In this subsection, we analyze intraday and overnight components of daily returns in the spirit of Lou et al. (2019). In their influential paper, authors document persistence in these returns over trading horizons up to 60 months. Put differently, stocks that performed well in the overnight portion of the day continue to have better overnight return performance in the future. There is also a reversing market force for the intraday section which creates a persistent inter-play between these returns. Accompanying results evince that stocks with lower overnight returns have higher intraday returns and vice versa. The findings of that study are tied to investor heterogeneity which is the opposite of representative agent models of the textbook approach. Individual investors are more active around opening hours whereas

Table 8:
Trading Strategies Based on Jump Classification

At the end of each month, we sort jump stocks according to their monthly cumulative overnight jump returns in ascending order where $D1$ is the first decile with the lowest returns and $D10$ is the last decile with the highest returns. We form value-weighted portfolios for each decile with one-month investment horizon (1M). This procedure is repeated every month and the means of the portfolio returns are recorded continuously. We implement long and short trading strategies for each decile along with a long/short strategy among $D1$, $D5$, and $D10$ decile portfolios. Raw returns are the mean value of portfolio returns over the analysis period. Table mainly reports FF4 alphas of trading strategies and Newey-West t-statistics with 12 lags. Our analyses cover 342 months over the period July 1993 - December 2021.

		PANEL A - Long Strategy		**PANEL B - Short Strategy**	
		1M		**1M**	
	Raw Return	**FF4 alpha**	**t**	**FF4 alpha**	**t**
D1	0.70%	-0.003	(-1.14)	-0.001	(-0.18)
D2	0.90%	-0.001	(-0.18)	-0.003	(-1.03)
D3	0.88%	-0.001	(-0.5)	-0.002	(-1)
D4	1.13%	0.002	(1.12)	-0.006	(-2.98)
D5	1.27%	0.005	(2.18)	-0.008	(-3.91)
D6	0.99%	0.001	(0.87)	-0.005	(-3.9)
D7	0.91%	0.000	(-0.07)	-0.004	(-2.25)
D8	0.90%	0.000	(-0.01)	-0.004	(-1.98)
D9	1.30%	0.003	(0.82)	-0.007	(-1.79)
D10	1.34%	0.003	(1.27)	-0.007	(-2.54)

		PANEL C - Long-Short Strategy	
		1M	
	Raw Return	**FF4 alpha**	**t**
D1-D10	-0.64%	-0.006	(-2.03)
D1-D5	-0.57%	-0.008	(-2.1)
D5-D10	-0.07%	0.001	(-0.43)

more professional institutional traders are more dominant in the second part of trading hours. This study is important in improving our understanding of overnight and intraday clientele and how their settled trading practices create a persistent market trend for these return components. In a very recent follow-up study, Akbas et al. (2022) analyze the intensity of this *tug of war* by looking at the number of days in a month with overnight and intraday return reversals. After forming the monthly ratio of reversal days, they scale it with the average of the preceding 12 months to reach a measure of abnormal frequency. Authors report that this monthly intensity has a predictive power for future returns when the reversals are associated with high opening prices. Their results show that stocks with high recurrence of 'positive overnight' - 'negative intraday' reversals have 0.92% higher returns in the subsequent month. They show that a high frequency of 'negative overnight' - 'positive intraday' reversals do not create any predictive power for next-month returns. This intensity work is similarly tied to the opposing clientele effects between noise traders and arbitrageurs.

Table 9:
Comparison of Jump and Non-Jump Stocks for 'Tug of War'

This table is a replication of Table 1 in Lou et al. (2019) with CAPM and FF4 alphas. We repeat the study separately for stocks without and with overnight jumps. At each month, we determine jump and non-jump stocks. Based on their monthly overnight and intraday return components, we sort them in ascending order, split them into deciles, and calculate the overnight and intraday return components in the next month. Later, the time series of these returns is regressed on the risk factors. We report the Newey-West t-statistic results for 12 lags in parenthesis. Panel A and Panel B tabulate results when stocks are ordered according to their overnight and intraday return components respectively. All the numbers are for the subsequent month. Our analyses cover 342 months over the period July 1993 - December 2021.

Panel A: Portfolios sorted by lagged one-month overnight cumulative returns

	Non-Jump Stocks				**Jump Stocks**			
	Overnight		**Intraday**		**Overnight**		**Intraday**	
Decile	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**
D1	-0.022	-0.021	0.036	0.039	0.002	0.002	0.011	0.014
	(-4.12)	(-4.04)	(4.42)	(4.62)	(0.29)	(0.39)	(1.38)	(1.75)
D10	0.046	0.046	-0.041	-0.039	0.030	0.030	-0.021	-0.021
	(6.34)	(6.14)	(-8.14)	(-7.17)	(4.18)	(4.05)	(-5.07)	(-4.49)
D10-D1	0.067	0.067	-0.077	-0.079	0.028	0.028	-0.033	-0.035
	(7.1)	(6.91)	(-7.98)	(-8.05)	(4.89)	(4.54)	(-3.83)	(-4.12)

Panel B: Portfolios sorted by lagged one-month intraday cumulative returns

	Non-Jump Stocks				**Jump Stocks**			
	Overnight		**Intraday**		**Overnight**		**Intraday**	
Decile	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**
D1	0.039	0.039	-0.034	-0.032	0.049	0.049	-0.044	-0.042
	(5.92)	(5.8)	(-7.41)	(-6.57)	(5.89)	(5.74)	(-6.66)	(-5.88)
D10	-0.009	-0.009	0.014	0.015	-0.011	-0.011	0.018	0.019
	(-2.16)	(-2.22)	(2.61)	(2.84)	(-2.18)	(-2.25)	(2.46)	(2.64)
D10-D1	-0.048	-0.048	0.048	0.047	-0.060	-0.060	0.062	0.061
	(-5.89)	(-5.84)	(7.13)	(6.86)	(-6.8)	(-6.66)	(6.52)	(6.21)

Our results are striking in deepening our knowledge of how overnight and intraday return components evolve and how the predictive power for the next month is altered for stocks with overnight information shocks. To check that, we replicate Table 1 in Lou et al. (2019) with CAPM and FF4 alphas and report the results in Table 9.

First of all, we split the stocks into overnight jump and non-jump groups each month. We separately sort them into deciles depending on their cumulative overnight and cumulative intraday return components for this month and form decile portfolios and implement a trading strategy that longs the highest decile and shorts the lowest one. Decile portfolio returns are the value-weighted returns every month. For non-jump stocks, we acquire quite the same results as Lou et al. (2019) and confirm the *tug of war* pattern. However, according to our findings tabulated in Panel A of Table 9, overnight portion of the jump stocks in $D10$ produce 1.6% less alpha in the next month whereas the intraday portion generates 1.8% better relative performance. Along with that, results for the stocks in $D1$ with the lowest overnight returns are also different in jump stocks. Although bad overnight performance persists in non-jump stocks, this is not the case for jump stocks; they have insignificant positive risk-adjusted overnight returns of 0.2%. For the intraday returns in the next month, jump stocks in $D1$ have 2.5% less alpha and their abnormal returns are insignificant at 5% significance level although that of non-jump stocks are highly significant with a t-statistics of 4.62. Moreover, long-short trading strategies produce comparably different results for jump stocks. In Panel A, the trading strategy of a long position in $D10$ and a short position in $D1$ in jump stocks produces 3.9% less risk-adjusted return for the overnight section compared to non-jump stocks whereas the same strategy incurs 4.2% less loss for the intraday portion. As can be seen from Panel A in Table 10, mean differences of jump and non-jump stock portfolios are highly significant for decile portfolios and for the trading strategy when portfolios are formed according to lagged cumulative overnight figures. These findings altogether mean that *tug of war* results of overnight jump stocks are significantly different than those of overnight non-jump stocks.

We report the results in Panel B when stocks are sorted according to their cumulative intraday returns. Our findings show that all of the results are magnified for overnight jump stocks compared to stocks with no overnight information shock. Jump stocks with the lowest cumulative intraday returns have 1% higher risk-adjusted overnight returns and 1% lower intraday returns compared to non-jump stocks in the next month. For $D10$, jump stocks have 0.2% lower overnight performance and 0.4% higher intraday returns. All of the results are statistically significant. The trading strategy of a long position in $D10$ and a short position in $D1$ in jump stocks produces 1.4% more risk-adjusted return for the intraday section compared to non-jump stocks whereas the same strategy incurs 1.2% more loss for the overnight portion. Again in Panel B of Table 10, we are providing the significance of mean differences when we form our portfolios based on the lagged cumulative intraday returns. Even though means are not statistically different for deciles, the trading strategy raw returns are still statistically different at 5% and 10% significance levels.

Table 10:
T-statistic Results for Mean Differences of Jump and Non-jump Stock Decile Portfolios

This table is complementary to Table 9 and tabulates the t-statistic results for mean differences of jump and non-jump stock decile portfolios and trading strategies. If we separately sort jump and non-jump stocks according to their lagged cumulative overnight (intraday) returns and look at the figures in the subsequent month, we will be constructing time series of one-month-ahead return figures for overnight and intraday portions for each decile and trading strategy. This table tells us if the means for jump and non-jump stocks are significantly different from each other in statistical terms. Our analyses cover 342 months over the period July 1993 - December 2021.

Panel A: Portfolios sorted by lagged one-month overnight cumulative returns		
	Overnight	**Intraday**
D1	5.60	-3.79
D10	-3.23	3.18
D10-D1	-7.09	6.70
Panel B: Portfolios sorted by lagged one-month intraday cumulative returns		
	Overnight	**Intraday**
D1	1.39	-1.22
D10	-0.84	0.93
D10-D1	-1.83	1.97

As we showed in Figure 2, stocks with overnight negative (positive) jumps have positive (negative) intraday cumulative returns on average. These information shocks intensify the return reversal behaviour compared to tranquil regular day reversals and that is also compatible with the results in Panel B of Table 9. In Panel A, results of $D1$ are not significant and do not conform to the basic *tug of war* pattern. Even though they have a positive intraday risk-adjusted return of 1.4% (significant at 10% significance level), the negativity in the overnight section does not extend to next month. Our *tug of war* findings are also consistent with Da et al. (2014) in which the authors show that momentum returns are more pronounced with continuous information stocks than stocks with discrete information. They report that investors are less attentive to frequently arriving small chunks of information and more heedful and alert to the intermittent but attention-grabbing news flows. Overnight jumps proxy information shocks in the wake of market closures and that fosters the discreteness of information in those stocks and debilitates the return continuation and momentum. In Panel A - Table 9, negative and positive overnight returns ($D1$ and $D10$) continue into the next month for non-jump stocks; negative (positive) overnight returns are followed by negative (positive) overnight returns as the information is less discrete. However, the discreteness of the information in jump stocks impedes the continuation of overnight negative returns into the next month; though lacks statistical significance, next month's overnight returns become positive (at least not negative anymore). In the same fashion, jump stocks with positive overnight returns ($D10$) in one month have shrunk four-factor alphas in the next month. Since the sorting scheme in Panel B is one-month cumulative intraday returns although the discreteness of information in our analysis emanates from overnight shocks, we see amplified alphas for jump stocks in all the intraday sections. As a consequence of the bloated monthly intraday returns driven by the overreaction to discrete overnight information arrivals, jump stocks have escalated returns in the intraday section for both extreme decile portfolios and the zero-cost portfolio.

All in all, our *tug of war* analysis has a focal point on information shocks to unearth dynamics of daily return components differently than Lou et al. (2019) who focus on regular overnight-intraday return reversals and Akbas et al. (2022) in which the starting point is the abnormal number of these return reversals in a month compared to previous 12 months.

5 Theoretical Foundations and Implications

Let $Y_t = ln(X_t)$ in time dimension $t \geq 0$ and let the triple $(\Omega, \mathcal{A}_t, \mathcal{P})$ represent the probability space for which Ω is the possibly observable outcome space, $\mathcal{A}_t$ represents the σ-algebra associated with the subsets of Ω and $\mathcal{P}$ is the measure assigning probabilities on $\mathcal{A}_t$. Let also $\mathcal{F}_t$ be the information filtration as sub-σ-algebra on $\mathcal{A}_t$ generated by a random process. In Equation 1, we explained the jump-diffusion process as $\int_0^t dX_t = \int_0^t \mu_s d_s + \int_0^t \sigma_s dB_s + \sum_{k=1}^{N_j^t} J_i \quad ; \quad \forall t \in [0, T]$.

A general form of a diffusion process for the price of a stock with drift and variance terms can be expressed as in Equation 11:

$$dX_t = \mu(X_t, t, ...)dt + \sigma(X_t, t, ...)dB_t \tag{11}$$

where drift term $\mu(X_t, t, ...) = \Upsilon$ and diffusive variance term $\sigma(X_t, t, ...) = \eta$ can also be functions of price levels, time, and any other variables that govern the stochastic price process. Notation-wise, a geometric Brownian motion with discontinuity adjustments for information shocks can be expressed as in Equation 12.

$$dX_t/X_t = \mu dt + \sigma dB_t + JdN_t \tag{12}$$

where J is the jump size and N_t is the counting process for randomly arriving jump incidences. In the absence of jumps, Equation 12 collapses to $dX_t = \mu X_t dt + \sigma X_t dB_t$. We create an overreaction/underreaction term to decompose the jump returns and isolate the rational component of price movement following information shocks. With surprising information flow, we let Λ_t be the rational rate of price movement and $\lambda_t = J_t - \Lambda_t$ be the movement due to psychological biases and both of these components are assumed to be orthogonal to dB_t with λ_t being a function of unobservable factors embedded all in Θ_t. If $\lambda_t = 0$, $\forall t \in [0, T]$, we conclude that all available information (including shocks) is rationally processed leading to accurate pricing. On the other hand, $\lambda_t > 0$, $\forall \Lambda_t > 0$ or $\lambda_t < 0$, $\forall \Lambda_t < 0$ means that market participants are prone to psychological biases and they overreact to information shocks whereas $\lambda_t < 0$, $\forall \Lambda_t > 0$ or $\lambda_t > 0$, $\forall \Lambda_t < 0$ implies that investors underreact to information shocks and create momentum in prices. Formally,

$$J_t \quad \text{level is flagged as} \quad \begin{cases} Overreaction, & \text{if } \lambda_t > 0 \quad \text{and} \quad \Lambda_t > 0, \forall t \in [0, T] \\ Overreaction, & \text{if } \lambda_t < 0 \quad \text{and} \quad \Lambda_t < 0, \forall t \in [0, T] \\ Rational & \text{if } \lambda_t = 0, \forall t \in [0, T] \\ Underreaction, & \text{if } \lambda_t > 0 \quad \text{and} \quad \Lambda_t < 0, \forall t \in [0, T] \\ Underreaction, & \text{if } \lambda_t < 0 \quad \text{and} \quad \Lambda_t > 0, \forall t \in [0, T] \end{cases} \tag{13}$$

A geometric Brownian model with this sort of decomposition will be

$$\frac{dX_t}{X_t} = \mu dt + \sigma dB_t + \Lambda dN_t + \lambda dN_t \tag{14}$$

in which the $dX_t^{rational}/X_t^{rational} = \mu d_t + \sigma dB_t + \Lambda dN_t$ governs rational component whereas $dX_t^{biased}/X_t^{biased} = \lambda dN_t$ represents the deviation from the rational price path as separate diffusion processes. $\forall t \in [0, T]$, $X_t = X_t^{rational} + X_t^{biased}$ and $Y_t = ln(X_t^{rational} + X_t^{biased})$. Applying Itô's Lemma[10] to $Y_t = f(X_t^{rational}, X_t^{biased}) = ln(X_t^{rational} + X_t^{biased})$ we get,

[10] See Appendix for the derivation

$$
\begin{aligned}
dY_t = (\mu - \frac{\sigma^2}{2} - \mu\Lambda dN_t - \mu\lambda dN_t)dt \\
+(\sigma - \sigma\Lambda dN_t - \sigma\lambda dN_t)dB_t \\
+(\Lambda + \lambda - \frac{\Lambda^2}{2} - \frac{\lambda^2}{2} - \Lambda\lambda)dN_t
\end{aligned}
\tag{15}
$$

Equation 15 outlines the process that the log-prices follow and it morphs into the widely-known form $dY_t = (\mu - \frac{\sigma^2}{2})dt + \sigma dB_t$ in the absence of jumps. It has useful interpretations. First, positive jumps ($\Lambda_t + \lambda_t > 0$) bring in additional downward drift in returns just like the diffusive variance term. On the other hand, negative jumps ($\Lambda_t + \lambda_t < 0$) make upward adjustments in the drift term. Second, in the case of overreaction, λ_t amplifies the size of the drift adjustment whereas underreaction implies that λ_t drags down the size of the drift adjustment due to Λ_t and λ_t having opposite signs and leading to $\mid J_t \mid < \mid \Lambda_t \mid$. Similar inferences can be made for the effects in diffusive variance term. Third, jump components wind up in the volatility term with the opposite sign meaning for instance that negative jumps intensify the variance of stocks. That negative association is in line with Bandi and Reno (2016) which document that large negative price discontinuities generally couple with positive discontinuities in variance. Volatility is not necessarily bad in the context of asset pricing as long as its surge serves for rational pricing as Fama (1989) stated after the market crash in October 1987[11]. In the context of the present study, we emphasize the role of the irrational jump component. The degree of reversal or the momentum magnitudes in follow-up returns - overreaction and underreaction - will be functions of that component λ_t. Broadly, mispricing-driven return predictability (see McLean and Pontiff (2016)) documented in the following chapter and its economic significance rest respectively on $\lambda_t \neq 0$ and γ which determines the degree of reversal.

On the other hand, a significantly different *tug of war* phenomenon in jump stocks documented in Section 4.4 is grounded in Λ_t and λ_t as they both lean on discrete information arrival. Jumps (combined effects of Λ_t and λ_t) impact the drift term, and diffusive variance and they also appear individually in Equation 15. Small but continuously arriving

[11]Eugene Fama highlights that "rational prices are not necessarily less volatile prices, and less volatile prices are not necessarily better than more volatile prices. The appropriate view of the October [1987] price shock depends critically on whether it was a rational response to changes in fundamental values"

information does not catch investors' attention as documented in Da et al. (2014) and unprocessed information creates deviation from rational prices creating abnormal returns for various trading strategies. With information shocks, inattention fades and investors become more vigorous leading to derailed prices being routed back to their rational path though not perfectly. Our findings in Panel A of Table 9 conform to this intuition: FF4 alphas are smaller in magnitudes in jump stocks compared to non-jump stocks. Portfolios formed according to lagged one-month overnight cumulative returns have smaller alphas in overnight jump stocks in Panel A. On the other hand, all of the magnitudes in Panel B are higher in jump stocks when portfolios are formed according to lagged one-month intraday cumulative returns. Since these are overnight jump stocks as opposed to stocks with intraday discontinuities, results are naturally altered.

Our study also has some implications for our understanding of market efficiency and for practitioners, especially the active portfolio managers, who look around for some insight into the future. First, there is still this ongoing debate on the concept to which the return predictability should be attributed. Is this concept the risk premium that is associated with some factors or is it investors' behavioral biases flawing the rationality? The present study contributes to cross-sectional return predictability literature by elaborating on investors' overreaction to overnight information shocks which come about in the form of overnight price jumps. Fama (1991) states that market efficiency is not testable because of the joint-hypothesis problem (it must be tested with a sound market equilibrium model) and the only testable thing is whether the information is reflected in prices *"properly"* or not. In order to claim market inefficiency, one should be sure that their model is not a bad model. In that regard, our findings and assertions may also be criticized and this post-jump return predictability can be attributed to a factor of *jump risk*. However, as widely documented, jumps are rare events and they come in as shocks in very short-time periods. As clarified in Jiang and Yao (2013), large price movements around these tiny windows are due to information shocks and barely linked to risk premium. Following this intuition, our study can also be classified as a short-window event study just like the ones elaborating on return dynamics around earnings announcements, the literature on flash crashes that bounce back in a very short time or other similar studies in the same spirit. To say the least, we cannot claim market inefficiency but we can say that the overnight information that surprises the market is not *"properly"* priced due to behavioral biases that defect the investor rationality premise.

Second, we are curious if the reported return predictability will decay after the findings are published. If our reported return predictability is grounded on rational expectations and is a reflection of risk in the market, we can then expect this overreaction mechanism to persist as discussed in McLean and Pontiff (2016). If, on the other hand, this pattern is due to mispricing, savvy investors can exploit this trend and then alleviate it in time. McLean and Pontiff (2016) documents a thorough analysis for 97 variables with cross-sectional predictive power and authors estimate 32% lower return after market participants become informed about the results of these publications. Regarding this issue, we conjecture that this overreaction incidence will stay in the market mainly for two reasons. The first one is related to the heterogeneously clustered investor groups along the day. As documented in Lou et al. (2019), there is a persistent interplay between individual and institutional/professional investors. Opening-hour orders are dominated by individual investors although the latter heavily trades in the second part of the day. This is actually in line with the settled market saying: *"The novice open the market and masters close it"*. Hence, unless the trading dynamics of these two groups converge with each other, we can expect this clientele effect to make this overreaction pattern perennial. Our second reasoning is linked to behavioral biases. It is a well-documented psychological fact that people overreact to information shocks. They can either make their decisions based on the worst-case scenario amid uncertainty and risky conditions or become overoptimistic and credulous when confronted with positive news. All in all, we expect this return pattern to be persistent and open to exploitation by astute market participants who are free of psychological biases and vigilant for these opportunities. Just to be clear, our guess of the long-lasting nature of this trend around overnight shocks is not tied to the risk premium concept but rather to the competing and unwavering behavioral forces of different clientele that are dominant in different parts of a specific trading day.

6 Conclusion

Investors' behavioral biases and their implications are heavily studied in the literature. This paper links overnight information shocks, short-term market overreactions, and subsequent return dynamics by looking at overnight price jumps in US equity markets. We show that investors' first reactions to unexpected overnight information flows are excessive and the direction of the price is reversed in the aftermath. With this persistent jump and reversal pattern, we can predict returns up to five days with statistical significance. Having a careful watch on the degree of reversal, we unearth that reversal ratio (*Reversal/Jump*) is considerably and significantly larger in stocks that are less costly to arbitrage. We also provide results of the contrarian trading strategy for a 1-month investment horizon to see if stocks with overnight positive jumps (winners) will experience relatively lower returns (losers) and vice versa. Stocks are sorted according to their lagged cumulative monthly jump returns and results of long/short strategy with extreme decile portfolios show that this bet will induce a statistically significant 0.6% loss rather than a profit. To enhance our knowledge on *tug of war* phenomenon which is recently documented by Lou et al. (2019), we replicate their study for jump and non-jump stocks. Expected overnight and intraday components of returns for the next month are significantly different in jump stocks. When stocks are sorted according to their intraday return components, *tug of war* pattern is amplified. When sorting is by overnight components, however, *tug of war* findings become considerably less in magnitude.

The quality of the information, the level of market ambiguity that surrounds investors and their association with short-term overreaction mechanisms have not been analyzed. In our follow-up study, we will analyze if this overreaction mechanism is exacerbated when ambiguity soars. The findings of that study will hopefully enhance our knowledge of the pillars of investor decision-making around information shocks.

Appendix

For the derivation of Equation 15, let first $f(p,q)$ be a multivariate function with variables p and q. Itô's Lemma for this function becomes

$$df = \frac{\partial f}{\partial p}dp + \frac{\partial f}{\partial q}dq + \frac{1}{2}\left[\frac{\partial^2 f}{\partial p^2}dp^2 + 2\frac{\partial^2 f}{\partial p \partial q}dpdq + \frac{\partial^2 f}{\partial q^2}dq^2\right] \tag{16}$$

Similarly, let Y_t be the log of observed prices X_t which is a function two different components $X_t^{rational}$ and X_t^{biased}: $Y_t = f(X_t^{rational}, X_t^{biased}) = ln(X_t^{rational} + X_t^{biased})$. Then,

$$dYt = \frac{\partial f}{\partial X_t^{rational}} dX_t^{rational} + \frac{\partial f}{\partial X_t^{biased}} dX_t^{biased} + \frac{1}{2}\Bigg[\frac{\partial^2 f}{\partial X_t^{rational2}} dX_t^{rational2} + 2\frac{\partial^2 f}{\partial X_t^{rational}\partial X_t^{biased}} dX_t^{rational} dX_t^{biased} + \frac{\partial^2 f}{\partial X_t^{biased2}} dX_t^{biased2}\Bigg] \tag{17}$$

Applying the partial first and second partial derivatives on $f(X_t^{rational}, X_t^{biased}) = ln(X_t^{rational} + X_t^{biased})$ yields

$$dYt = \frac{1}{X_t^{rational} + X_t^{biased}} dX_t^{rational} + \frac{1}{X_t^{rational} + X_t^{biased}} dX_t^{biased} - \frac{1}{2}\Bigg[\frac{1}{(X_t^{rational} + X_t^{biased})^2} dX_t^{rational2} + 2\frac{1}{(X_t^{rational} + X_t^{biased})^2} dX_t^{rational} dX_t^{biased} + \frac{1}{(X_t^{rational} + X_t^{biased})^2} dX_t^{biased2}\Bigg] \tag{18}$$

Remember that $\frac{dX_t}{X_t} = \mu dt + \sigma dB_t + \Lambda dN_t + \lambda dN_t$, $X_t = X_t^{rational} + X_t^{biased}$ and $dX_t = dX_t^{rational} + dX_t^{biased}$. If we let $\Psi = \frac{dX_t}{X_t}$ for brevity, Equation 18 becomes

$$\begin{aligned} dYt &= \frac{\Psi}{X_t} dX_t^{rational} + \frac{\Psi}{X_t} dX_t^{biased} - \frac{1}{2}\Bigg[\frac{\Psi^2}{X_t^2} dX_t^{rational2} + 2\frac{\Psi^2}{X_t^2} dX_t^{rational} dX_t^{biased} \\ &+ \frac{\Psi^2}{X_t^2} dX_t^{biased2}\Bigg] = \Psi\left[\frac{dX_t^{rational} + dX_t^{biased}}{dX_t}\right] - \frac{1}{2}\left[\frac{\Psi}{dX_t} dX_t^{rational} + \frac{\Psi}{dX_t} dX_t^{biased}\right]^2 \\ &= \Psi - \frac{1}{2}\Psi^2 \end{aligned} \tag{19}$$

Ψ^2 term can be formulated as

$$\begin{aligned} \Psi^2 = \mu^2 dt^2 + (2\mu dt + \sigma dB_t)\sigma dB_t + (2\mu dt + 2\sigma dB_t + \Lambda dN_t)\Lambda dN_t + \\ (2\mu dt + 2\sigma dB_t + 2\Lambda dN_t + \lambda dN_t)\lambda dN_t \end{aligned} \tag{20}$$

where the components $\mu^2 dt^2$ and $2\mu dt \sigma dB_t$ will be zero as they contain the higher orders of dt. We also replace the term $\sigma^2 dB_t^2$ with $\sigma^2 dt$ as an adjustment for quadratic variation ($dB_t^2 = dt$). Hence, the diffusion process for the log of prices becomes

$$
\begin{aligned}
dY_t = \Psi - \frac{1}{2}\Psi^2 = (\mu - \frac{\sigma^2}{2} - \mu\Lambda dN_t - \mu\lambda dN_t)dt \\
+(\sigma - \sigma\Lambda dN_t - \sigma\lambda dN_t)dB_t \\
+\Lambda dN_t \\
+\lambda dN_t \\
-(\frac{\Lambda^2}{2} + \frac{\lambda^2}{2} + \Lambda\lambda)dN_t^2
\end{aligned} \tag{21}
$$

where $dN_t^2 = dN_t \; \forall t \in [0, T]$, as the number of jumps at any time will either be 0 or 1. Then,

$$
\begin{aligned}
dY_t = (\mu - \frac{\sigma^2}{2} - \mu\Lambda dN_t - \mu\lambda dN_t)dt \\
+(\sigma - \sigma\Lambda dN_t - \sigma\lambda dN_t)dB_t \\
+(\Lambda + \lambda - \frac{\Lambda^2}{2} - \frac{\lambda^2}{2} - \Lambda\lambda)dN_t
\end{aligned} \tag{22}
$$

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