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

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Abstract

Using a very large data set with more than 9,700 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 up to five days. For negative and positive overnight jumps, results are significant with Newey-West adjusted t-stats and robust to various model specifications. We also show that 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 0.8% of risk-adjusted loss in 1-month investment horizon. These together connote that documented overreaction and return reversal are short-term market phenomena. With novel findings for jump stocks, present study also builds a new avenue for overnight and intraday expected returns in the recently renowned *tug of war* literature which rests 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 literatures by paying special attention to investor behaviours around price discontinuities and post-shock return dynamics.

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

Keywords: Price Jumps; Overreaction; Return Predictability

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1. Introduction

"Much of the real world is controlled as much by the tails of distributions as by means or averages: by the exceptional, not the mean; by the catastrophe, not the steady drip; by the very rich, not the middle class. We need to free ourselves from 'average' thinking."

Philip W. Anderson – 1977 Nobel Prize Laureate in Physics

Investor overreaction over different investment horizons and its reciprocal interaction with expected returns have attracted special attention and relevant literature has surfaced varying return patterns from three-to-five years of cycles to time spans of minutes during a specific trading day. Guided by the experimental psychology on people's inclination to overreact to information shocks, De Bondt and Thaler (1985) report that 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. Analyzing positive and negative information shocks for S&P500 firms with daily prices, Frank and Sanati (2018) report reversals (overreaction) after positive shocks whereas stocks continue drifting (underreaction) when the news is negative. In one strand of the literature, these return predictability patterns are linked to flaws in investors' cognitive judgements 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, literature is still indecisive about the dominant return patterns in the post-shock period as highlighted in Frank and Sanati (2018), Tetlock (2014) and in references therein.

In this paper, we take heed of Philip W. Anderson's advice and become advertent to *exceptional* events within the context of stock markets: basically to the sharp price movements and return dynamics in the aftermath. Needless to say, finance literature is in consensus for the inclusion of extreme price changes to data generating process. Over the past decades, 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.

Our contribution to extant literature will be in six main facets. First, to the best of our knowledge, this will be the first study which connects overnight price jumps and their reversals with short-term overreaction discussions in stock markets. Our research provides more clarification on investors' reaction to unexpected positive and negative overnight information flows and consequent return jumps. Though Jiang and Zhu (2017) provide evidence of underreaction for information shocks which end up as daily jumps, we are analyzing extreme price movements that become ephemeral to certain extent after market correction. After detecting both positive and negative overnight jumps, we essentially examine the cumulative return dynamics in the follow-up period up to five days and identify statistically significant return predictability with 5.76 and 3.70 Newey-West t-statistics respectively for positive and negative discontinuities in the first day after jumps. This relationship is also significant up to five days with t-statistics numbers progressively declining to 3.30 and 2.26 respectively. In short, this study extends our understanding of the price behaviours directly after the overnight shocks.

Second, inspired by the work of Atilgan et al. (2020), we take a profound look at costly arbitrage conditions and different levels of jump and reversal magnitudes in stocks. With focal attention to reversed jump fraction, we show that arbitrageurs abstain from price correction for stocks with high idiosyncratic risks whereas roughly 50% and 33% of jump magnitudes are reversed back for stocks with lowest idiosyratic risk figures respectively after negative and positive jumps in the first day. In that sense, our study brings in novel explanations for why overreactions in some stocks become more stagnant compared to some other equities. Our findings are detailed in Section 3.3.

Third, we build a new avenue in recently burgeoning 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 on the "tug of war" intensity during a month. Our study brings in another perspective to this return predictability in the light of extreme price movements. We show that abnormal returns in overnight and intraday returns with 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 4.2% 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 4.6% less loss for the intraday return component. Generally, *tug of war* results are intensified for jump stocks when stocks are sorted according to their intraday return components. When the ordering is according to overnight return component, we even report that the settled return continuation pattern in *tug of war* (negative cumulative overnight returns being followed by negative overnight returns in the subsequent month) is broken for stocks in the lowest decile. We present our findings in Section 3.5.

Forth and with equal importance, we 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 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 0.8% loss with 2.26 absolute Newey-West t-statistics. On the other hand, momentum trading strategy resulted in 0.4% risk-adjusted gain with non-assertive t-statistics of 1.22. These pricing behaviours imply that overreaction and return reversal after overnight jumps are short-term market phenomena.

Fifth, we comprehensively analyze the driving forces and tractability of these abrupt movements on the market level. This paper reports that there is a statistically significant inverse relationship between the incidence of jumps and the level of conditional market volatility in overnight, intraday and daily positive jumps as well as overnight and intraday negative jumps. This is actually the essence of jump detection because large price fluctuations are credited to volatility rather than to jumps amid wavering market conditions. We also control for firm-specific and market-wide liquidity measures and show that negative intraday and daily jumps are also linked to liquidity shocks in line with the common market sense. Both positive and negative overnight discontinuities have no statistically significant relationship with prevailing market liquidity which is also compatible with our expectation prior to the analysis since the dominant force for overnight section is the information shocks.

Last, although jumps are sporadic extraordinary events for individual stocks, we show that aggregated negative and positive jump returns on market level are time-dependent and predictable. Hence we also provide an extensive analysis for the stochastic nature of aggregated jump dynamics over the past three decades. As opposed to a jump study on market indexes where the effect of simultaneous positive and negative jumps are canceled, we are reporting the lag-dependence in composite positive and composite negative jumps for overnight, intraday and daily components and testing the collective forecastability of positive and negative jumps on a market level.

Our study stands at the intersection of jump, overreaction and return predictability literatures. Inspired with the works of Jiang and Zhu (2017), Lou et al. (2019) and Akbas et al. (2022), we first detect overnight jumps in stock returns and examine price behaviors in the following period. We look at return predictability with monthly cumulative overnight jump returns in the spirit of Lou et al. (2019) and Akbas et al. (2022). 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. Our curiosity for the noteworthiness of jump returns also emanates from Kapadia and Zekhnini (2019) which document that annualized return of a stock is cumulatively made of the price jumps in 4 days over a year and from Jiang and Yao (2013) which 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. Like Jiang and Zhu (2017), we use jumps as a proxy for special information which triggers surprisal in stock returns. This choice is also compatible with the informational contents in a complete day cycle in the sense that firm specific news is generally disclosed after closing bell and priced in largely by individual investors as trading commences in the next morning (Lou et al. (2019)). Moreover, it is a documented fact that 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). However, our research differs from the above studies in some stark aspects.

First, we detect overnight jumps in its own time series and mark the days with overnight return surprisal as opposed to Jiang and Zhu (2017) which identify daily jumps and decompose these close-to-close returns into its overnight and intraday components. Our filtering methodology provides us with special information when there is no daily jump. We additionally run our jump detection test for close-to-close returns to see return surprisal in daily price movements and their alignment with overnight jumps. Strikingly, only 11% percent of overnight jump days have also jumps in daily returns. That is also consistent with descriptive statistics that intraday reversals are quite salient during the days when no daily jump is identified. That said, this argument does not imply any straightforward return level comparison since jumps are relative magnitudes in 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. Succinctly, although Jiang and Zhu (2017) contribute to underreaction literature by focusing on return continuation, we fill a gap in overreaction camp with a focal point on information shocks over the night and reversing market reaction in the aftermath.

Second, as opposed to Lou et al. (2019) which accumulate all overnight returns in their return predictability analysis, we calculate monthly cumulative returns to pay particular attention to stocks and days only with overnight information shocks. This way, we keep investor reactions under magnifying glass around jumps and gauge the return predictability for jump stocks. Moreover, based on the mean of cumulative intraday returns after overnight jumps, we document that intraday return reversals are more outstanding after negative overnight jumps compared to positive information shocks. We conjecture it as a reflection of individual investors' risk averseness and oversensitivity to negative shocks which is later corrected by institutional investors. Agents' asymmetric overreaction response in positive and negative jump cases may also be related with the ambiguity in arriving information or ambiguity in widespread market conditions. Epstein and Schneider (2008) document that investors adapt themselves to worst-case scenario under poor information quality and react more intensely to bad ambiguous news than they do for 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.

Third, Atilgan et al. (2020) show that investors underreact to bad news and do not properly process the embedded information. They overprice stocks with extreme losses and that creates a momentum in the left-tail returns. However, our study is different than theirs in some 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 as in the case of VaR and ES.

Notes on Clientele Effect

Research on overnight and intraday components of close-to-close daily returns has heralded new avenues for clientele relevance, content of information, and return predictability. In asset-pricing context, non-homogeneous investor beliefs and preferences reveal itself 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 other). 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 continuation of market returns while other group anticipate reversals in market trends. Author argues that fat tails in return distributions are a result of pessimist and optimist investors clustered in 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 sixty-months horizon. Specifically, higher overnight returns in a month are succeeded with higher overnight returns and lower intraday return 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 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) which report that individual investors -after markets open- snap up stocks which 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 monthly intensity of "tug of war" and show how higher intensity cross-sectionally predicts higher future returns. 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.

Rest of the paper is organized as follows. In Section 2, we provide the details of data and filtering mechanisms together with the applied methodology for jump identification and time series construction. Section 3 is reserved for empirical findings. Implications for market participants are detailed in Section 4. Section 5 concludes.

2. Data and Methodology

2.1. Data

Since price jumps are low probability episodes in nature, it is crucial to keep the database as large as possible to come up with generalizable conclusions as opposed to being contended with stocks only within the well-known headline indexes.[1] We circumvent this rare-event challenge with a very large sample of 9,718 stocks listed on NYSE, AMEX and NASDAQ during the whole June 1992-December 2021 period or in-between.

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

[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.

track companies and securities over the trading history respectively. In our main analysis, we use PERMCO identifiers those 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 previous day closing prices to ensure the jump detection not halted. In case an intraday jump is identified on that day, we eliminate it during our robustness check. If the closing price is missing, CRSP sets bid-ask average as the closing price on that day. We keep these closing prices in the main analysis. In our robustness check however, jumps linked to these prices are also excluded from our results. We keep stocks which 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 assure 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 9718 stocks from US markets. Sieved CRSP data is 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 CRSP dataset. It is basically the natural logarithm of 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 the calculated at the end of 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 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 data

[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 referred as "idiosyncratic volatility puzzle". See Hou and Loh

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 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 with 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 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 (L): 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.

2.2. Methodology

2.2.1. Jump Identification

We start with the representation of a stock price model with semi-martingale process embodying both diffusive continuous movements and jump components. Let Y_t stand for the log-price process of a stock in a probability space with available information set $\mathcal{F}_t$ to all parties. For a unit period of

(2016) for a comprehensive recent discussion on present explanations in the literature and the extent this puzzle had been solved thus far.

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

[4] This adjustment factor is originally based on a 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

[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:

$$Y_t = Y_0 + \int_0^t a_s d_s + \int_0^t \sigma_s dB_s + \sum_{k=1}^{N_j^t} J_i \quad ; \quad \forall t \in [0, T] \tag{1}$$

where the first three terms ($Y_0 + \int_0^t a_s d_s + \int_0^t \sigma_s dB_s$) constitute continuous stochastic price path with initial price (Y_0), drift term (a), diffusive variance (σ) and standard Brownian motion (B). 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,

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

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

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 Sheppard; 2003 for further discussion and Huang and Tauchen; 2005 for extensions). Herewith, jump variation component and its relative contribution to quadratic variation are straightforward in 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 Jiang and Oomen (JO) test which rests on 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 via dividing each return with 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, asymptotic distribution of $\mathcal{L}_i$ is a standard normal whereas presence of jumps leads to elevated test statistics. They offer below metric to decide on whether to reject 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.

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

2.2.2. Time Series Construction

We create three different return time series for overnight, intraday and daily periods and detect the jumps separately for each interval. Intraday returns are simply calculated with closing and opening prices in 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;

$$r_i^{ovn} = \frac{r_i + 1}{r_i^{int} + 1} - 1 \tag{8}$$

$$r_{mc}^{ovn} = \prod_{i=1} (r_i^{ovn} + 1) - 1 \quad \text{and} \quad r_{mc}^{int} = \prod_{i=1} (r_i^{int} + 1) - 1 \quad \text{and} \quad r_{mc} = \prod_{i=1} (r_i + 1) - 1 \tag{9}$$

where r_i^{ovn}, r_i^{int} and r_i are respectively the overnight, intraday and daily returns of stock i and r_{mc}^{ovn}, r_{mc}^{int} and r_{mc} are monthly cumulative returns for the same periods in order. Monthly cumulative jump returns and cumulative returns of non-jump days are calculated in the same way.

3. Empirical Findings

3.1. Statistical Properties of Jumps

First of all, our findings evince that overnight period can be classified as the period of discontinuities whereas intraday period is the period of volatilities. As tabulated in Table 1, number of jumps along close-to-open semi-cycles are extremely larger than jumps during the trading hours. Figure 1 also reveals this phenomenon for the whole data period. Another striking findings is the shrinking number of jumps for all sections of the day. Pertinent to the nature of jumps, we have three hypothesis.

Hypothesis 1: *Number of jumps should be inversely related with conditional market volatility.*

As the volatility of stocks/markets increases, large price movements will be credited to volatility as opposed to jumps. Local variation in returns is standardized by realized bi-power variation. In a period with larger price swings, realized bi-power variation will also be larger and it will make the

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. *Int. Ret.* in the table stands for intraday returns after overnight jumps.

Panel A								
OVERNIGHT JUMPS	**Numbers**	**Mean**	**Median**	**Int. Ret.<0**	**Int. Ret.>0**	**Int. Ret.=0**	**Int. Ret. with Opposite Sign**	**Int. Ret. with Same Sign**
Total	433,785	0.4%	-0.9%					
Negative	230,555	-6.7%	-4.6%	58,432	105,618	66,505	46%	25%
Positive	203,230	8.4%	5.0%	100,497	60,873	41,860	49%	30%

Panel B								
INTRADAY JUMPS	**Numbers**	**Mean**	**Median**	**Ovn. Ret.<0**	**Ovn. Ret.>0**	**Ovn. Ret.=0**	**Ovn. Ret. with Opposite Sign**	**Ovn. Ret. with Same Sign**
Total	159,171	2.9%	2.5%					
Negative	72,756	-10.8%	-8.3%	31,128	40,242	1,386	55%	43%
Positive	86,415	14.4%	9.1%	48,091	36,427	1,897	56%	42%

Panel C								
DAILY JUMPS	**Numbers**	**Mean**	**Median**	**Int. Ret.<0**	**Int. Ret.>0**	**Int. Ret.=0**	**Int. Ret. with Opposite Sign**	**Int. Ret. with Same Sign**
Total	136,430	3.6%	3.6%					
Negative	63,934	-14.8%	-11.7%	55,708	4,489	3,737	7%	87%
Positive	72,496	19.9%	13.0%	4,273	65,475	2,748	6%	90%

jump test statistic lower. Hence, we expect lower number of local returns marked as discontinuous price movements.

Since we employ different analysis for positive and negative jumps, we measure conditional market volatility via E-GARCH due to Nelson (1991). It captures asymmetric nature of the volatility and model parameters can be estimated without non-negativity constraints. In its parsimonious form, conditional volatility equation is formed as in the following way.

$$ln(\sigma_t^2) = \beta_0 + \beta_1 ln(\sigma_{t-1}^2) + \beta_2\Big[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \frac{\sqrt{2}}{\sqrt{\pi}}\Big] + \Upsilon\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} \tag{10}$$

where β_2 is for symmetric information and Υ measures the sensitivity to asymmetries. After getting the daily conditional volatility, we aggregate it monthly by taking the mean for every month. To generate our market return time series, we make use of all the stocks in our analysis and calculate value-weighted daily market returns; with market capitalization being our weights. Notation-wise,

$$r^m_{vw,t} = \sum_{i=0}^{A_t} r_{i,t} w_{i,t} \tag{11}$$

where A_t is the number of stocks, $r^m_{vw,t}$ is value-weighted market return, $r_{i,t}$ is stock-specific return and $w_{i,t}$ is the weight at day t.

Hypothesis 2: *Number of jumps should have some degree of correlation with stock specific liquidity conditions and the mechanics of market micro-structure.*

Think of two stocks; one with sparsely populated order book (a midcap stock) and the other with densely populated price levels where investors descend on for various reasons (a blue-chip stock). If there are unquoted or sparsely quoted price levels, level of price movement becomes larger for a sufficiently large transaction in the former. To put it differently, slippage becomes larger if the order book absorbs incoming orders through higher number of price tick movements. Amihud illiquidity measure simply captures the degree of price movement for a certain trading amount and it is one of the widely used asset specific illiquidity measures. To set the level of monthly illiquidity for each stock, we first take the mean of daily illiquidity measures in that month. For monthly market illiquidity metric, we calculate value weighted Amihud illiquidity measure across the whole dataset.

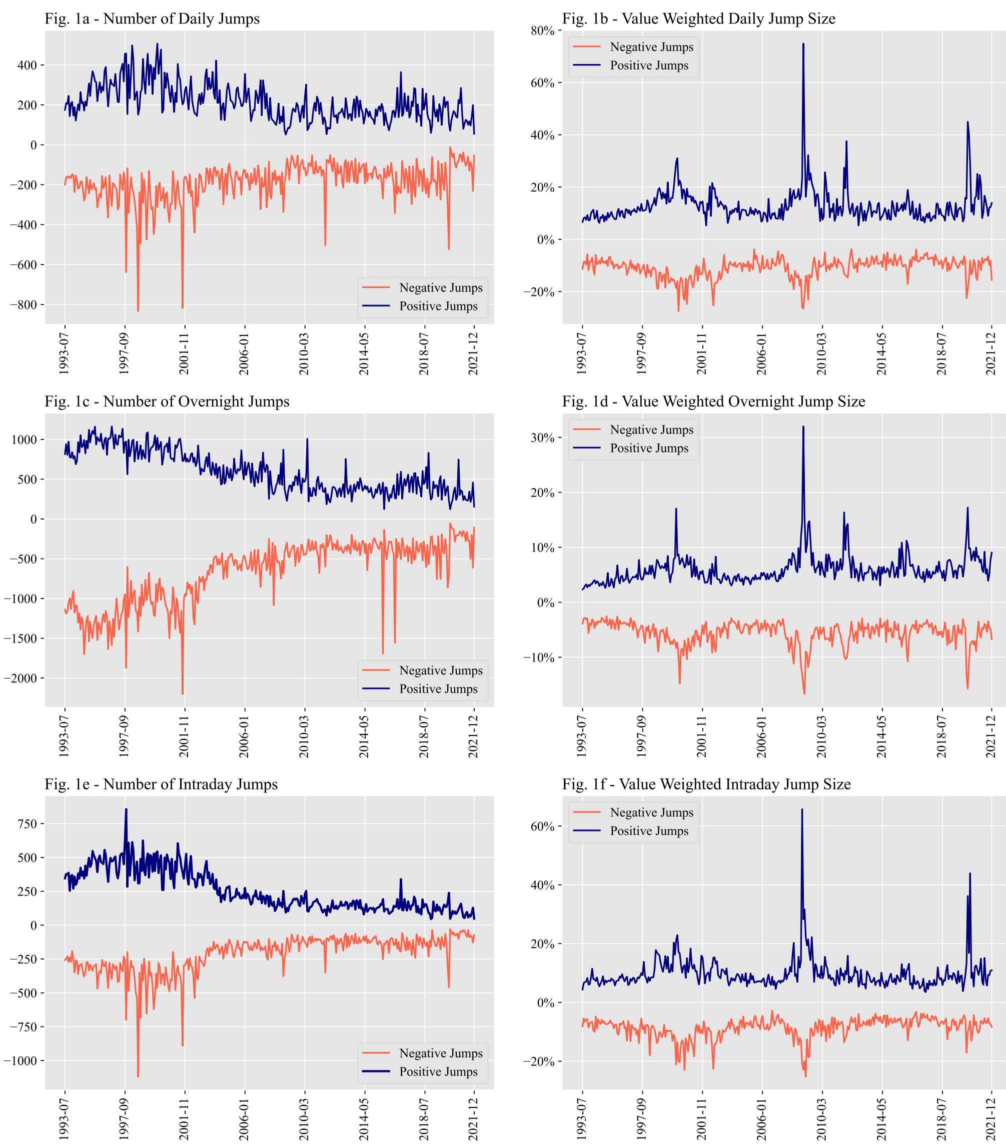
Hypothesis 3: *Number of jumps should have some degree of correlation with market-wide liquidity conditions.*

This hypothesis is quite straightforward: if market-wide liquidity dries, stocks become more prone to abrupt price changes. Pástor and Stambaugh (2003) document that aggregate liquidity level is a priced systemic risk factor and assets are sensitive to pervasive shocks in liquidity. Problem becomes acute especially during crises periods and that is why investors are eager to pay higher for stocks that stumble relatively less amid dearth of liquidity in these chaotic market conditions.

We analyze three hypothesis with the following econometric model. We run 6 separate OLS regressions for overnight, intraday and daily price discontinuities in both positive and negative jump occasions.

$$JN_t = \alpha_t + \beta_1 AI_t + \beta_2 PS_t + \beta_3 CVOL_t + \beta_4 DV_t + \varepsilon_t \tag{12}$$

Figure 1: Montly Jump Numbers and Value-Weighted Jump Returns.



Notes: On the left panel, graph are created by accumulating numbers for each month. Number of negative jumps are multiplied by -1 to make the shrinking jump incidences more visible. For the right panel, we calculate value-weighted jump returns within each month. As the weight, we use market value of the equity at the end of each month.

where JN_t is the percent variation in jump numbers, AI_t is the value-weighted monthly Amihud Illiquidity for all stocks, PS_t is the Pastor-Stambaugh market-wide liquidity measure[5] and $CVOL_t$ is conditional market volatility. We also include an intercept dummy DV_t to capture variations in jumps during very exceptional periods. For each dependent variable, DV_t is 1 when the current observation is outside 4σ boundaries and 0 otherwise.

Table 2
Jump Numbers and Driving Factors

Table reports the regression outputs for Eq.12 for negative and positive jumps corresponding to overnight, intraday and daily sections. JN_t denotes the percent change in the jump numbers for each month. Absolute Newey-West t-statistic values for 12 lags are reported in parenthesis. To control for firm-specific and market-wide liquidity, we use monthly Amihud Illiquidity (AI_t) and Pastor-Stambaugh (PS_t) non-traded liquidity factor measures. Stock-specific AI_t values are calculated by taking the mean of daily numbers in that month. Market AI_t is then computed via the value-weighted average of individual measures. To account for monthly conditional volatility ($CVOL_t$), we first calculate value-weighted daily market returns of all stocks in our dataset and generate daily volatility series by applying E-GARCH. For monthly conditional volatility series, we take the mean at each period.

	PANEL A		**PANEL B**		**PANEL C**	
	Overnight Jumps		**Intraday Jumps**		**Daily Jumps**	
Negative Jumps						
Dep. Variable	JN_t		JN_t		JN_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**
const	0.18	(3.78)*	0.14	(4.30)*	0.21	(4.48)*
AI_t	-0.25	-0.80	-0.24	(0.82)	-0.64	(1.64)
PS_t	-0.35	-0.90	-0.91	(2.59)*	-1.05	(2.31)*
$CVOL_t$	-11.46	(2.72)*	-7.12	(2.29)*	-8.17	(1.49)
DV_t	3.20	(6.19)*	2.05	(62.36)*	2.38	(28.9)*
$Adj.R^2$	0.35		0.12		0.11	
Positive Jumps						
Dep. Variable	NJ_t		NJ_t		NJ_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**
const	0.13	(4.05)*	0.09	(3.32)*	0.19	(5.35)*
AI_t	0.20	(0.65)	0.31	(1.28)	0.30	-0.90
PS_t	-0.27	(1.04)	-0.33	(1.15)	0.03	(0.08)
$CVOL_t$	-10.90	(3.82)*	-7.91	(2.66)*	-14.75	(4.04)*
DV_t	1.84	(12.57)*	1.73	(8.77)*	1.74	(13.78)*
$Adj.R^2$	0.24		0.25		0.14	

Results are reported in Table 2 and there are striking findings compatible with our expectations before the analysis. Firstly, conditional volatility is statistically significant in all regression outputs except for the daily negative jumps. The sign of the coefficient is also in line with the rationale. For given levels of market and stock-specific liquidity measures, number of jumps are inversely related with the level of conditional market volatility. As previously stated, integrated volatility gets larger

[5]We use WRDS for Pastor-Stambaugh non-traded liquidity factor.

if a return is preceded with sufficiently large returns within the realized bi-power variation window and that makes the jump identification statistic lower. Secondly, variation in negative intraday and negative daily jumps are inversely related with market-wide liquidity conditions with t-statistics 2.59 and 2.31 respectively. Simply put, abrupt negative price movements can be driven by liquidity shortages. For positive intraday and daily jumps however, market liquidity seems to have no significant effect. This implies that upward price movements are relatively more continuous with liquidity moving in an out. Moreover, market liquidity measure is not statistically significant for both overnight negative and overnight positive jumps. These results conform to what we expected before the analysis since the overnight return dynamics are mostly dependent on information flows whereas intraday section is open to liquidity shocks and shocks related with trading practices.

3.2. 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 cross-sectional regression results for the first day just after the overnight information shocks and report the results in Table 4 and Table 5. For Table 4, we run Eq. 13 starting from the most parsimonious version and expand it by adding our control variables one at a time. Table 5 tabulates the results for all stocks and for stock groups sorted on BM ratios. Correlation numbers are reported in Table 3.[6]

$$\begin{aligned} CDR_t = \alpha + \beta_1 CJR_t + \beta_3 IVOL_t + \beta_2 SIZE + \beta_8 BM + \beta_4 LEV + \\ \beta_5 RET_{t-1,t-5} + \beta_6 RET_{t-6,t-11} + \beta_7 AI_t + \varepsilon_t \end{aligned} \tag{13}$$

where CDR_t is the monthly cumulated post-jump daily returns and CJR_t is the cumulative overnight jump returns preceding the daily returns of our interest. Observe that subscripts tell us only the return cumulation frequency rather than a simultaneous relationship. We know that CJR_t is the lagged cumulative jump returns by construction. For the definition of other regressor variables,

[6] Negative jumps are not 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 with information shocks. 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 high correlation with $IVOL$ for both positive and negative jumps.

Table 3

Descriptive Statistics and Correlation Matrix

This table tabulates descriptive statistics and correlations between the variables in our monthly cross-sectional regressions. We calculate the figures at each month, construct a time series and average them. CJR^{+} and CJR^{-} are respectively the monthly cumulated positive and negative jump returns, $IVOL$ 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 2.1 for the detailed explanations of variables.

PANEL A: Descriptive Statistics

	CJR_t^{+}	CJR_t^{-}	$IVOL_t$	$SIZE_t$	BM_t	LEV_t	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
Mean	0.11	-0.10	0.04	19.17	-0.62	1.11	0.05	0.07	21.03
Median	0.07	-0.07	0.03	18.99	-0.52	0.81	0.01	0.02	0.48
St.Dev.	0.17	0.10	0.04	2.02	1.07	0.91	0.38	0.45	157.57
Min	0.00	-0.66	0.00	14.54	-6.05	0.00	-0.81	-0.81	0.00
Max	2.30	-0.003	0.46	25.54	4.04	5.67	3.35	4.33	2708.35
Skew.	5.90	-2.21	4.69	0.38	-0.58	1.27	2.67	3.10	12.23
Kurto.	61.80	6.84	41.79	-0.16	4.70	2.26	24.52	29.79	191.55
25th Per.	0.04	-0.14	0.02	17.66	-1.15	0.41	-0.14	-0.15	0.02
75th Per.	0.12	-0.04	0.05	20.53	0.00	1.69	0.17	0.20	4.02

PANEL B: Correlations (Negative Jumps)

	CJR_t^{-}	$IVOL_t$	$SIZE_t$	BM_t	LEV_t	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
CJR_t^{-}	1.00							
$IVOL_t$	-0.67	1.00						
$SIZE_t$	0.23	-0.32	1.00					
BM_t	-0.01	0.05	-0.39	1.00				
LEV_t	0.08	-0.06	-0.12	-0.06	1.00			
$RET_{t-1,t-5}$	0.10	-0.13	0.03	-0.04	0.01	1.00		
$RET_{t-6,t-11}$	0.06	-0.09	0.09	-0.16	0.00	0.00	1.00	
AI_t	-0.17	0.23	-0.24	0.12	0.04	-0.07	-0.05	1.00

PANEL C: Correlations (Positive Jumps)

	CJR_t^{+}	$IVOL_t$	$SIZE_t$	BM_t	LEV_t	$RET_{t-1,t-5}$	$RET_{t-6,t-11}$	AI_t
CJR_t^{+}	1.00							
$IVOL_t$	0.71	1.00						
$SIZE_t$	-0.25	-0.34	1.00					
BM_t	0.04	0.05	-0.36	1.00				
LEV_t	-0.04	-0.06	-0.10	-0.09	1.00			
$RET_{t-1,t-5}$	-0.11	-0.13	0.05	-0.05	0.00	1.00		
$RET_{t-6,t-11}$	-0.08	-0.10	0.10	-0.15	-0.01	0.02	1.00	
AI_t	0.14	0.20	-0.23	0.11	0.04	-0.07	-0.05	1.00

see Section 2.1. We perform separate regressions for negative and positive jump incidences.

The most striking result in Table 4 is the significance of CJR_t in almost all forms of regression outputs with a negative sign for both negative and positive overnight jumps. Moreover, coefficients for negative and positive jump incidences are quite solid respectively around -0.80 and -0.37 through the columns (2)-(8). In the largest model set-up, Newey-West t-stat values are respectively 3.70 and 5.76. Apparently, our CJR_t variable is orthogonal to all control variables and these findings all together mean that cumulative jump returns have a distinctive and significant predictive

Table 4

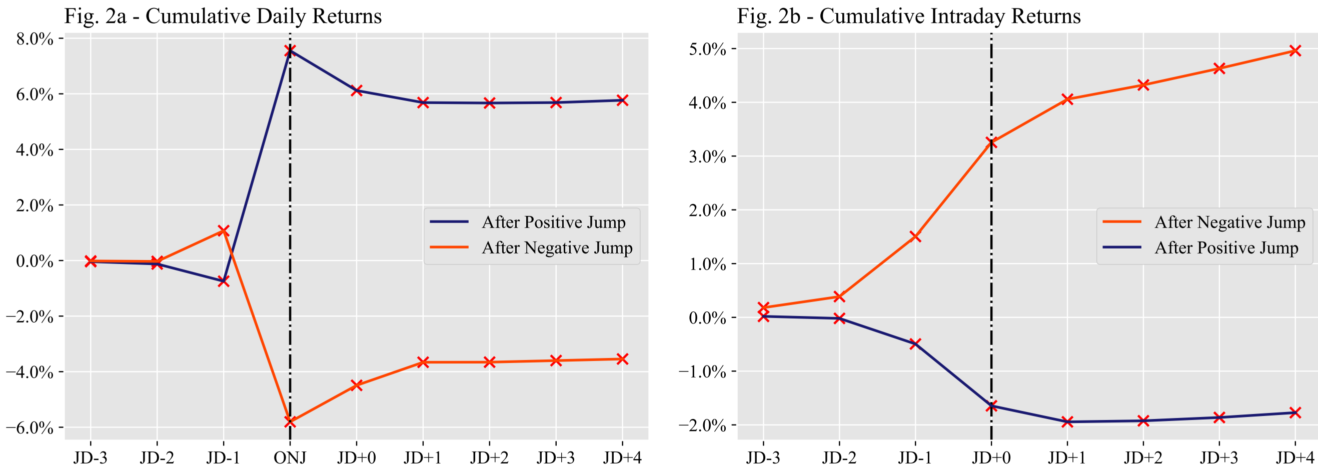
Cross-Sectional Regressions for Return Predictability

At each month we calculate cumulative jump and cumulative intraday returns for stocks with overnight negative and positive jumps. We then run cross-sectional regressions for each month where dependent variable is the post-jump intraday return IR_t which is actually the cumulative return at the end of the first day following the jump. Table populates averaged coefficient estimates and 12-lag Newey-West t-statistics from the monthly regressions. t-stats are reported in absolute terms. From column (2) to (8), we add each firm specific control variables 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. CJR^+ and CJR^- are respectively the monthly cumulated positive and negative jump returns, $IVOL$ 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. Regression coefficients of BM_t, LEV_t, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are multiplied by 100. See Section 2.1 for the detailed explanations of variables.

PANEL A: Negative Jumps								
Dep. Variable: IR_t	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	coef.	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**
CJR_t^-	-0.47	-0.79	-0.80	-0.80	-0.80	-0.80	-0.80	-0.80
	(1.92)	(3.49)	(3.59)	(3.61)	(3.61)	(3.63)	(3.64)	(3.7)
$IVOL_t$		-1.38	-1.55	-1.55	-1.55	-1.58	-1.59	-1.61
		(2.88)	(3.18)	(3.18)	(3.19)	(3.25)	(3.27)	(3.27)
$SIZE_t$			-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
			(3.49)	(3.1)	(3)	(3.01)	(3.01)	(2.95)
BM_t				0.31	0.34	0.29	0.24	0.24
				(0.03)	(0.02)	(0.01)	(0.09)	(0.11)
LEV_t					0.05	0.06	0.05	0.06
					(0.11)	(0.09)	(0.1)	(0.12)
$RET_{t-1,t-5}$						-1.70	-1.72	-1.70
						(0.42)	(0.43)	(0.43)
$RET_{t-6,t-11}$							-0.19	-0.24
							(0.45)	(0.46)
AI_t								0.00
								(0.36)
Intercept	-0.03	0.00	0.14	0.13	0.13	0.13	0.13	0.13
	(0.08)	(1.43)	(3.56)	(3.25)	(3.05)	(3.05)	(3.06)	(3.02)
$Adj.R^2$	0.09	0.18	0.21	0.21	0.21	0.22	0.22	0.23

PANEL B: Positive Jumps								
Dep. Variable: IR_t	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	coef.	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**	**coef.**
CJR_t^+	-0.11	-0.37	-0.37	-0.37	-0.37	-0.37	-0.36	-0.37
	(2.51)	(5.38)	(5.57)	(5.6)	(5.64)	(5.67)	(5.69)	(5.76)
$IVOL_t$		1.29	1.44	1.45	1.46	1.48	1.50	1.51
		(4.03)	(4.56)	(4.6)	(4.64)	(4.74)	(4.81)	(4.84)
$SIZE_t$			0.01	0.01	0.01	0.01	0.01	0.01
			(4.86)	(4.63)	(4.56)	(4.58)	(4.57)	(4.53)
BM_t				0.16	0.19	0.22	0.27	0.28
				(0.55)	(0.64)	(0.7)	(0.83)	(0.85)
LEV_t					0.19	0.19	0.19	0.20
					(0.66)	(0.65)	(0.66)	(0.67)
$RET_{t-1,t-5}$						1.56	1.58	1.55
						(1.07)	(1.1)	(1.08)
$RET_{t-6,t-11}$							1.02	1.01
							(0.89)	(0.89)
AI_t								0.00
								(0.2)
Intercept	0.00	-0.03	-0.19	-0.19	-0.20	-0.20	-0.20	-0.20
	(0.31)	(3.53)	(5.15)	(5)	(4.81)	(4.86)	(4.85)	(4.83)
$Adj.R^2$	0.08	0.29	0.32	0.33	0.33	0.34	0.34	0.35

Figure 2: Overreaction Path

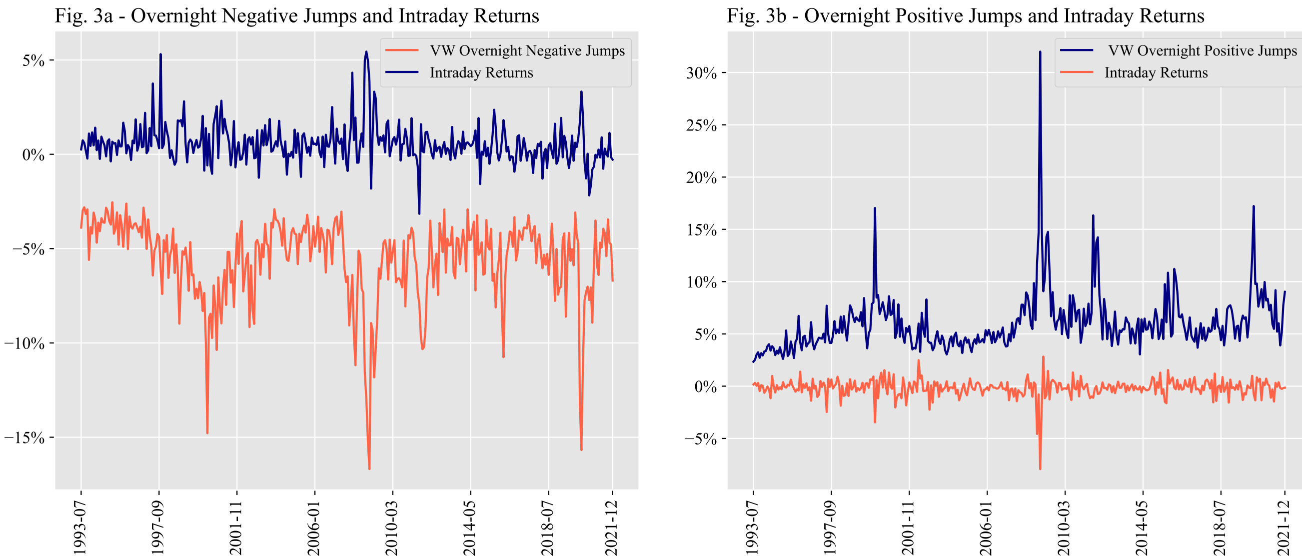


Notes: This graph shows overreaction to overnight information shocks. Left panel plots the mean of the cumulative daily returns around negative and positive overnight price jumps whereas the right panel unravels the mean of cumulative intraday returns. 4.2% of consecutive overnight positive jumps are 1 day apart from each other. 1.8%, 2.0%, 1.6% and 1.5% of consecutive overnight positive jumps are 2, 3, 4 and 5 days apart from each other respectively. These ratios are 4.8%, 3.4%, 3.0%, 2.9% and 2.7% in the same order for consecutive negative overnight jumps.

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 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, intraday portion of cumulative returns are 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 with an opposite sign average daily return. Actually, we can see that daily cumulative return is 1.07% on day $JD - 1$ in the case of negative jumps and trend is upward just like the post-jump period and -0.7% in the case of positive jumps and trend is downward just like the post-jump period.

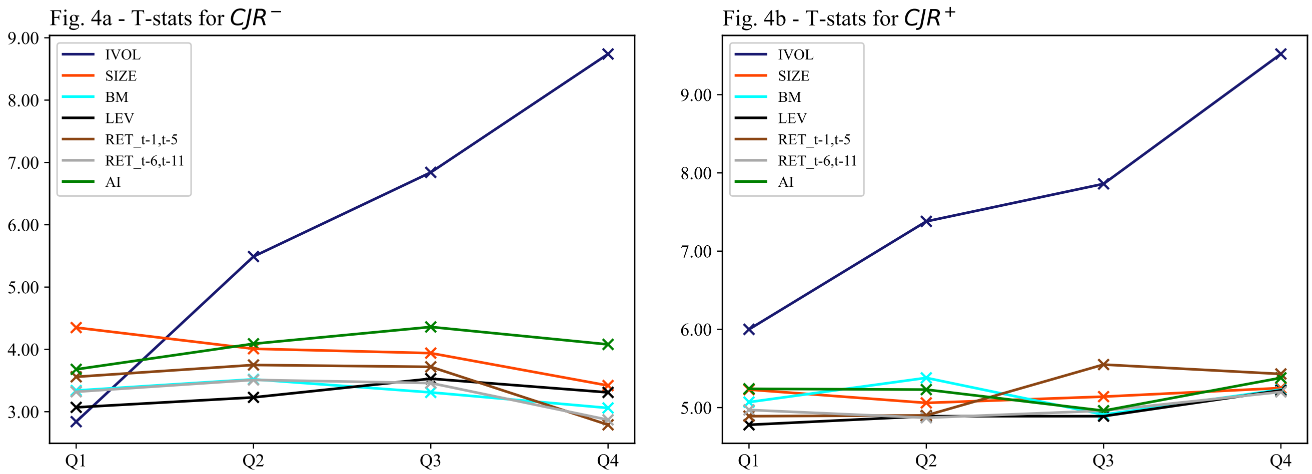
Figure 3: Overnight Jumps and Intraday Returns



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

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 statistically significant effect on the return behaviours around these short-term overreaction episodes. These 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. On the other hand, CJR_t is statistically significant in all regression results as a factor of information shocks. $SIZE$ factor even loses its significance after at the third day at 5% significance level. Table 5 documents results of 1-day cross-sectional return predictability. To check the significance of CJR in different stock groups, we repeat our analysis by forming quartile portfolios based on each control variable. At each month, we sort jump stocks in descending order according to the values of control variables, split them in quartiles and run cross sectional regressions. Hence, we employ this Fama-MacBeth regression set-up for 28 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 quartile portfolio for all control variables, but for $IVOL$. For $IVOL$, significance of CJR visibly boosts towards the quartile with lowest values. Table 5 tabulates Fama-MacBeth regression outputs when stocks are sorted according to their BM ratios. All in all, our findings evince that cross-sectional return predictability around these short-event windows (the very few days after overnight jumps) are explained partly by firm characteristics and partly by our cumulative jump return factor that proxies information shocks.

Figure 4: Overnight Jumps and Intraday Returns



Notes: This graph shows the Newey-West adjusted t-statistics values for CJR in 1-day cross-sectional return predictability Fama-MacBeth regressions. At each month, we sort overnight jump stocks in descending order based on the values of control variables and form quartile portfolios. With 7 control variables, we employ Fama-MacBeth regressions for 28 different portfolio formation rules. CJR^- and CJR^+ are respectively the monthly cumulated negative and positive jump returns, $IVOL$ 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 2.1 for the detailed explanations of variables.

Our analysis also evinces striking results for the control variables. First, coefficient of $IVOL_t$ is negative for all days in Panel A of Table 6 and statistically significant at 5% level after three days and at 10% level after four 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 its 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 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

Table 5
Intraday Return Predictability After Overnight Jump

At each month we calculate cumulative jump and cumulative intraday returns for stocks with overnight negative and positive jumps. We then run cross-sectional regressions for each month. Table populates averaged coefficient estimates and 12-lag Newey-West t-statistics from the monthly regressions. t-stats are reported in absolute terms. Results are reported for all jump stocks on the leftmost columns. Apart from that, we sort stocks based on their BM values at each month, form 4 different jump portfolios and run the regressions separately. Q1 denotes the results for highest BM ratios and Q4 stands for stocks in the last quartile. This table reports results only for the first day after jumps. CJR^{+} and CJR^{-} are respectively the monthly cumulated positive and negative jump returns, $IVOL$ 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. Regression coefficients of BM_t, LEV_t, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are multiplied by 100. See Section 2.1 for the detailed explanations of variables.

PANELA:NegativeJumps	**AllStocks**		**Q1**		**Q2**		**Q3**		**Q4**	
Dep.Variable	IR_t		IR_t		IR_t		IR_t		IR_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	0.13	(3.02)	0.08	(1.27)	0.13	(2.11)	0.17	(2.56)	0.19	(2.89)
CJR_t^{-}	-0.80	(3.7)	-1.08	(3.34)	-0.62	(3.52)	-0.62	(3.31)	-0.56	(3.06)
$IVOL_t$	-1.61	(3.27)	-1.64	(2.57)	-1.57	(2.93)	-1.91	(3.53)	-1.87	(3.41)
$SIZE_t$	-0.01	(2.95)	0.00	(1.21)	-0.01	(1.93)	-0.01	(2.43)	-0.01	(2.77)
BM_t	0.24	(0.11)	-0.58	(0.22)	-0.76	(0.13)	-0.20	(0.21)	-0.47	(0.39)
LEV_t	0.06	(0.12)	-0.53	(0.3)	-0.26	(0.5)	0.10	(0.1)	-0.19	(0.14)
$RET_{t-1,t-5}$	-1.70	(0.43)	-3.61	(0.4)	-0.98	(0.18)	-1.29	(0.39)	-1.04	(0.31)
$RET_{t-6,t-11}$	-0.24	(0.46)	2.75	(0.1)	-0.54	(0.16)	-0.86	(0.34)	-0.67	(0.26)
AI_t	0.00	(0.36)	-0.00	(0.29)	0.00	(0.18)	0.02	(0.67)	0.02	(1.15)
$Adj.R^2$	0.23		0.31		0.31		0.31		0.29	

PANELB:PositiveJumps	**AllStocks**		**Q1**		**Q2**		**Q3**		**Q4**	
Dep.Variable	IR_t		IR_t		IR_t		IR_t		IR_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	-0.20	(4.83)	-0.16	(2.21)	-0.16	(2.94)	-0.19	(3.2)	-0.25	(3.91)
CJR_t^{+}	-0.37	(5.76)	-0.37	(5.07)	-0.41	(5.38)	-0.40	(4.91)	-0.39	(5.23)
$IVOL_t$	1.51	(4.84)	1.39	(4.45)	1.66	(5.3)	1.71	(4.88)	1.68	(4.49)
$SIZE_t$	0.01	(4.53)	0.01	(1.92)	0.01	(2.62)	0.01	(3.11)	0.01	(3.85)
BM_t	0.28	(0.85)	-0.74	(0.83)	0.59	(0.23)	1.00	(0.49)	0.34	(0.56)
LEV_t	0.20	(0.67)	0.19	(0.42)	0.28	(0.68)	0.01	(0.17)	0.14	(0.26)
$RET_{t-1,t-5}$	1.55	(1.08)	2.20	(0.89)	1.59	(0.65)	1.50	(0.59)	1.10	(0.59)
$RET_{t-6,t-11}$	1.01	(0.89)	1.95	(0.89)	1.30	(0.61)	0.95	(0.46)	0.54	(0.4)
AI_t	-0.00	(0.2)	0.00	(0.08)	0.02	(0.18)	-0.00	(0.59)	-0.01	(0.07)
$Adj.R^2$	0.35		0.37		0.38		0.38		0.38	

variables in Panel B of Table 6 are not necessarily composed of negative returns. However, the average reaction after positive overnight jumps are 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. Left panel in Figure 2 shows cumulative daily returns whereas the right panel is generated with cumulative returns of intraday components.[7] Hence, we interpret the positive sign of $IVOL_t$ as again compatible with literature as opposed to disappearance of idiosyncratic volatility puzzle. It can also be interpreted as stocks with higher $IVOL_t$ numbers perform better when cumulative

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

returns are negative on average. We can make the similar interpretation for $SIZE$ as well.

Table 6
Daily Return Predictability After Overnight Jump

At each month we calculate cumulative jump and cumulative daily returns for stocks with overnight negative and positive jumps. We then run cross-sectional regressions for each month. Table populates averaged monthly coefficient estimates and 12-lag Newey-West t-statistics from the monthly regressions. t-stats are reported in absolute terms. Dependent variable $1D_t$ is the intraday return just after the overnight jump. For the other days, dependent variable represents cumulative return upto that day after jump incidence. CJR^+ and CJR^- are respectively the monthly cumulated positive and negative jump returns, $IVOL$ 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. Regression coefficients of BM_t, LEV_t, $RET_{t-1,t-5}$ and $RET_{t-6,t-11}$ are multiplied by 100. See Section 2.1 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**
$Intercept$	0.13	(3.02)	0.14	(2.71)	0.13	(2.45)	0.13	(2.24)	0.11	(2)
CJR_t^-	-0.80	(3.7)	-0.81	(3.44)	-0.76	(2.87)	-0.70	(2.51)	-0.69	(2.26)
$IVOL_t$	-1.61	(3.27)	-1.37	(2.46)	-1.20	(2.07)	-1.03	(1.75)	-0.88	(1.6)
$SIZE_t$	-0.01	(2.95)	-0.01	(2.74)	-0.01	(2.46)	-0.01	(2.26)	-0.01	(2)
BM_t	0.24	(0.11)	0.41	(0.25)	0.49	(0.29)	0.46	(0.32)	0.56	(0.34)
LEV_t	0.06	(0.12)	0.24	(0.29)	0.26	(0.26)	0.24	(0.22)	0.32	(0.24)
$RET_{t-1,t-5}$	-1.70	(0.43)	-1.17	(0.21)	-1.20	(0.26)	-1.07	(0.26)	-0.85	(0.25)
$RET_{t-6,t-11}$	-0.24	(0.46)	0.12	(0.2)	0.14	(0.16)	0.14	(0.14)	0.23	(0.08)
AI_t	0.00	(0.36)	0.00	(1.74)	0.00	(1.89)	0.00	(1.48)	0.00	(1.38)
$Adj.R^2$	0.23		0.26		0.22		0.20		0.19	

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**
$Intercept$	-0.20	(4.83)	-0.23	(4.14)	-0.24	(3.82)	-0.25	(3.55)	-0.25	(3.34)
CJR_t^+	-0.37	(5.76)	-0.35	(4.43)	-0.35	(4.02)	-0.34	(3.62)	-0.33	(3.3)
$IVOL_t$	1.51	(4.84)	1.48	(3.59)	1.50	(3.25)	1.54	(3.01)	1.50	(2.8)
$SIZE_t$	0.01	(4.53)	0.01	(3.96)	0.01	(3.66)	0.01	(3.42)	0.01	(3.21)
BM_t	0.28	(0.85)	0.26	(0.55)	0.29	(0.56)	0.36	(0.54)	0.34	(0.55)
LEV_t	0.20	(0.67)	0.09	(0.23)	0.13	(0.28)	0.15	(0.26)	0.10	(0.22)
$RET_{t-1,t-5}$	1.55	(1.08)	1.65	(0.87)	1.66	(0.8)	1.66	(0.73)	1.69	(0.68)
$RET_{t-6,t-11}$	1.01	(0.89)	1.01	(0.67)	1.02	(0.62)	1.01	(0.57)	0.92	(0.52)
AI_t	-0.00	(0.2)	-0.00	(0.98)	-0.00	(1)	-0.00	(0.91)	-0.00	(0.85)
$Adj.R^2$	0.35		0.25		0.22		0.19		0.17	

3.3. Costly Arbitrage as a Source of Reversal Magnitude

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 [8]. Atilgan et al. (2020) report that stocks with higher left-tail risk have anomalously lower future returns since investors

[8]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.

underreact to bad news and continue demanding those stocks and thereby create overpricing. The gist of our paper is however the investor overreaction to negative and positive overnight information shocks which is later reversed to some extent. 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 one of the most crucial arbitrage costs especially when it is combined with extreme noise trading. In Table 7 and Table 8, we delve into price reversals and their association with the stocks' idiosyncratic risks as well with as idiosyncratic illiquidity. We expect the fraction of jump returns that is reversed to be lower for stocks with higher levels of idiosyncratic volatility and illiquidity.

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 descending order according to their $IVOL$ numbers in that month and their AI figures on the jump day. We split the sorted stock list in quintiles and analyze their jump and reversal patterns thoroughly. $Q1$ contains the most risky and illiquid stocks whereas $Q5$ encloses stocks with 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 7 and Table 8 tabulates results when sorting is based on $IVOL$ levels. Findings explicitly reveals that jump magnitudes for $Q1$ stocks are quite large and significantly different than those of stocks in $Q5$. That is in line with our expectation before the analysis. Strikingly, 49% of the negative overnight jump is reversed for $Q5$ stocks just on the jump day whereas this fraction is only 14% for $Q1$ stocks. At the end of second and third day after the jump, reversal fraction is respectively 57% and 58% for $Q5$ stocks although the numbers are 26% and 27% for $Q1$. For positive overnight jumps, we show that 39% of the jump is reversed in the first day after overnight jump for $Q5$ stocks whereas this fraction is only 3% for stocks with highest idiosyncratic risks. Reversal fraction is 40% and 38% after two and three days after jump for $Q5$ stocks while the fractions for $Q1$ stocks are 7% and 8% respectively. We also document that these reversal fractions for negative and positive jump incidences are significantly different from each other.

Table 7

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 descending order according to their Idiosyncratic Volatility ($IVOL$) levels during that month and their Amihud Illiqudity (AI) figures on jump day and split the sorted stocks in quintiles. *Quintile 5* 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 absolute t-statistics values below in parenthesis.

NEGATIVE 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	2.8%	-14.9%	**0.14**	4.5%	-14.9%	**0.26**	4.5%	-14.9%	**0.27**
Quintile 2	3.7%	-8.3%	**0.26**	4.3%	-8.3%	**0.34**	4.3%	-8.3%	**0.34**
Quintile 3	2.0%	-6.0%	**0.32**	2.5%	-6.0%	**0.41**	2.5%	-6.0%	**0.42**
Quintile 4	1.9%	-4.5%	**0.39**	2.2%	-4.5%	**0.48**	2.2%	-4.5%	**0.48**
Quintile 5	1.7%	-3.1%	**0.49**	1.9%	-3.1%	**0.57**	1.9%	-3.1%	**0.58**
Q5-Q1	-1.1%	11.8%	**0.35**	-2.6%	11.8%	**0.31**	-2.6%	11.8%	**0.31**
	(0.89)	(49.20)	**(9.31)**	(2.09)	(49.20)	**(7.90)**	(2.08)	(49.20)	**(7.78)**

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	2.0%	-8.0%	**0.26**	4.6%	-8.0%	**0.56**	4.7%	-8.0%	**0.58**
Quintile 2	2.1%	-7.5%	**0.29**	2.8%	-7.5%	**0.41**	2.8%	-7.5%	**0.40**
Quintile 3	1.6%	-7.5%	**0.24**	1.8%	-7.5%	**0.27**	1.7%	-7.5%	**0.27**
Quintile 4	3.5%	-7.5%	**0.20**	3.6%	-7.5%	**0.21**	3.7%	-7.5%	**0.22**
Quintile 5	2.7%	-6.2%	**0.40**	2.5%	-6.2%	**0.36**	2.5%	-6.2%	**0.36**
Q5-Q1	0.7%	1.8%	**0.14**	-2.1%	1.8%	**-0.20**	-2.2%	1.8%	**-0.21**
	(1.38)	(9.10)	**(3.52)**	(4.46)	(9.10)	**(5.33)**	(4.53)	(9.10)	**(5.42)**

We replicate our analysis by sorting stocks according to their AI figures at each month and document our findings for negative and positive overnight jumps in Panel B of Table 7 and Table 8. For the negative jumps, 40% of jump magnitude is reversed on jump day for $Q5$ stocks whereas this 26% for the most illiquid group. The difference in these fractions is also statistically significant. For second and third day after the negative overnight jumps, reversal fraction in $Q1$ stocks surpasses that of $Q5$ stocks. For positive overnight jumps, 33% of the jump is reversed in the first day for $Q5$ stocks although it is 13% for $Q1$ stocks and this difference is statistically significant. For second and third day, reversal fraction for $Q5$ stocks are around 28% and it is slightly above that of $Q1$ stocks with 27% reversal ratio.

Our study is crucial in shedding light on investor overreaction and the resultant mispricing.

Findings presented in this subsection is also critical in demonstrating us the arbitrageur reactions. We report that arbitrageurs are less willing to step in and correct the mispricing for stocks which are costlier to arbitrage. In other words, reversal is more pronounced for jump stocks when the associated arbitrage cost is lower.

Table 8
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 descending order according to their Idiosyncratic Volatility ($IVOL$) levels during that month and their Amihud Illiqudity (AI) figures on jump day and split the sorted stocks in quintiles. *Quintile 5* 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 absolute t-statistics values below in parenthesis.

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	-0.7%	22.0%	**0.03**	-1.5%	22.0%	**0.07**	-1.7%	22.0%	**0.08**
Quintile 2	-1.6%	9.9%	**0.15**	-2.0%	9.9%	**0.18**	-2.0%	9.9%	**0.18**
Quintile 3	-1.6%	7.2%	**0.19**	-1.8%	7.2%	**0.22**	-1.8%	7.2%	**0.22**
Quintile 4	-1.6%	5.5%	**0.27**	-1.7%	5.5%	**0.29**	-1.8%	5.5%	**0.28**
Quintile 5	-1.4%	3.4%	**0.39**	-1.4%	3.4%	**0.40**	-1.4%	3.4%	**0.38**
Q5-Q1	-0.7%	-18.6%	**0.35**	0.1%	-18.6%	**0.33**	0.3%	-18.6%	**0.31**
	(3.43)	(28.77)	**(31.75)**	(0.34)	(28.77)	**(23.02)**	(0.76)	(28.77)	**(18.45)**

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	-1.3%	9.9%	**0.13**	-2.7%	9.9%	**0.27**	-3%	10%	**0.27**
Quintile 2	-1.5%	10.2%	**0.14**	-1.6%	10.2%	**0.16**	-2%	10%	**0.16**
Quintile 3	-1.0%	10.3%	**0.09**	-1.2%	10.3%	**0.08**	-1%	10%	**0.08**
Quintile 4	-0.9%	10.1%	**0.07**	-1.1%	10.1%	**0.05**	-1%	10%	**0.05**
Quintile 5	-2.2%	7.3%	**0.33**	-1.9%	7.3%	**0.28**	-2%	7%	**0.28**
Q5-Q1	-0.9%	-2.7%	**0.19**	0.7%	-2.7%	**0.02**	0.8%	-2.7%	**0.01**
	(6.56)	(7.89)	**(14.88)**	(4.97)	(7.89)	**(1.09)**	(4.24)	(7.89)	**(0.63)**

3.4. Trading Strategies

Investors are implementing dynamic trading strategies with various expectations into 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 highest returns. Afterwards, 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 reversal. As tabulated in Table 9, a contrarian trading strategy for the stocks with lowest negative overnight jump returns incures -0.2% abnormal return though the Newey-West statistics is 0.71 in absolute terms. However, a contrarian strategy for positive overnight jump stocks in last decile results in -0.7% abnormal return with a significant t-statistics of -2.80. A combined contrarian trading strategy which longs $D1$ and shorts $D10$ portfolios ends up -0.8% of abnormal return with again a significant t-statistics of -2.26. This combined trading method incurs 0.9% abnormal loss with a significant t-statistics of -2.22 if we instead use $D1$ and $D5$ portfolios.

On the other hand, a relative strength trading strategy which buys stocks that performed well ($D10$) and sells the ones that incurred losses ($D1$) ends in 0.4% abnormal return with Newey-West t-statistics of 1.22. Results for $D5$-$D1$ is 0.5% with t-statistics of 1.28. With these figures in hand, we conclude that a contrarian trading strategy which classifies stocks based on the past overnight cumulative jump returns incurs an abnormal loss of 0.8% with statistical significance while a relative strength strategy yields 0.4% abnormal returns though we are not confident with the number in statistical terms. 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 portfolio returns are considered. The overreaction pattern in the wake of overnight information shocks morph into drifting return when the next-month investment portfolios are considered.

3.5. “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 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

Table 9
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 mean 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. Data period is Jul. 1993 - Dec. 2021.

		PANEL A - Long Strategy		**PANEL B - Short Strategy**	
		1M		**1M**	
	Raw Return	**FF4 alpha**	**t**	**FF4 alpha**	**t**
D1	0.8%	-0.002	-0.71	-0.002	-0.51
D2	0.8%	-0.001	-0.44	-0.002	-0.79
D3	0.9%	-0.001	-0.42	-0.003	-1.11
D4	1.1%	0.001	0.75	-0.005	-2.59
D5	1.2%	0.005	2.14	-0.008	-3.83
D6	1.0%	0.001	1.07	-0.005	-4.00
D7	0.9%	0.000	-0.03	-0.004	-2.33
D8	0.7%	-0.002	-1.16	-0.002	-1.16
D9	1.5%	0.005	1.32	-0.008	-2.34
D10	1.3%	0.004	1.49	-0.007	-2.80

		PANEL C - Long/Short Strategy	
		1M	
	Raw Return	**FF4 alpha**	**t**
D1-D10	-0.6%	-0.008	-2.26
D10-D1	0.6%	0.004	1.22
D1-D5	-0.48%	-0.009	-2.22
D5-D1	0.48%	0.005	1.28
D5-D10	-0.07%	-0.001	-0.26
D10-D5	0.07%	-0.003	-0.85

intraday returns and vice versa. Findings of that study are tied to investor heterogeneity which is the opposite of representative agent models of textbook approach. Individual investors are more active around opening hours whereas 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 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 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 opposing clientele effect between noise traders and arbitrageurs.

Table 10

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 and based on their monthly overnight and intraday return components, we sort them in ascerding order, split into deciles and calculate the overnight and intraday return components in the next month. We report absolute values of Newey-West t-statistic results for 12 lags in paranthesis. 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 subsequent month.

Panel A: Portfolios formed according to lagged one-month overnight cumulative returns

	Non-Jump Stocks				Jump Stocks			
	Overnight		Intraday		Overnight		Intraday	
	CAPM	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**
D1	-0.022	-0.022	0.037	0.041	0.002	0.003	0.012	0.015
	(4.18)*	(4.1)*	(4.51)*	(4.69)*	(0.33)	(0.47)	(1.47)	(1.79)
D10	0.046	0.046	-0.041	-0.040	0.028	0.029	-0.019	-0.019
	(6.53)*	(6.26)*	(8.31)*	(7.32)*	(3.82)*	(3.72)*	(5.08)*	(4.79)*
D10-D1	0.067	0.066	-0.080	-0.082	0.025	0.024	-0.034	-0.036
	(7.32)*	(7.1)*	(8.2)*	(8.29)*	(4)*	(3.7)*	(3.78)*	(4.06)*

Panel B: Portfolios formed according to lagged one-month intraday cumulative returns

	Non-Jump Stocks				Jump Stocks			
	Overnight		Intraday		Overnight		Intraday	
	CAPM	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**	**CAPM**	**FF4 alpha**
D1	0.039	0.040	-0.035	-0.033	0.050	0.051	-0.045	-0.042
	(5.91)*	(5.77)*	(7.4)*	(6.43)*	(5.19)*	(5.1)*	(7.11)*	(6.35)*
D10	-0.008	-0.009	0.013	0.015	-0.011	-0.011	0.017	0.018
	(2.06)*	(2.13)*	(2.57)*	(2.8)*	(2.4)*	(2.45)*	(2.5)*	(2.68)*
D10-D1	-0.050	-0.050	0.046	0.046	-0.063	-0.063	0.060	0.059
	(5.87)*	(5.84)*	(6.94)*	(6.64)*	(6.31)*	(6.14)*	(6.63)*	(6.35)*

Our results are striking in deepening our knowledge on 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 the Table 1 in Lou et al. (2019) with CAPM and FF4 alphas and report the results in Table 10. First of all, we split the stocks into overnight jump and non-jump groups at 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 at every month. For non-jump stocks, intuition of the results is quite the same as Lou et al. (2019). However, according to our findings tabulated in Panel A of Table 10, overnight portion of the jump stocks in $D10$ produce 1.7% less alpha in the next month whereas intraday portion generates 2.1% 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 0.3%. For the intraday returns in the next month, jump stocks in $D1$ have 2.6% less alpha and their abnormal returns are insignificant at 5% significance level. For Panel A, the trading strategy of a long position in $D10$ and a short position in $D1$ in jump stocks produces 4.2% less risk-adjusted return for overnight section compared to non-jump stocks whereas the same strategy incurs 4.6% less loss for the intraday portion. As can be seen from Panel A in TABLE 7, 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 1.1% higher risk-adjusted overnight returns and 0.9% lower intraday returns compared to non-jump stocks in the next month. For $D10$, jump stocks have 0.2% lower overnight performance and 0.3% 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 1.3% more risk-adjusted return for intraday section compared to non-jump stocks whereas the same strategy incurs 1.3% more loss for the overnight portion. Again in Panel B of TABLE 7, we are providing 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 returns are still statistically different at 10% significance level.

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

Table 11
T-statistic Results for Mean Differences of Jump and Non-jump Stock Decile Portfolios

This table is complementary to Table 10 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.

PanelA:
Portfolios sorted by lagged one-month overnight cumulative returns

	Overnight	**Intraday**
D1	5.75	-3.9
D10	-3.43	3.68
D10-D1	-7.1	7.26

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

	Overnight	**Intraday**
D1	1.22	-1.15
D10	-1.04	0.92
D10-D1	-1.72	1.88

behaviour compared to tranquil regular day reversals and that is also compatible with the results in Panel B of Table 10. In Panel A, results of $D1$ are not significant and do not conform to basic *tug of war* pattern. Even though they have positive intraday returns of 1.5% (significant at 10% significance level), the negativity in the overnight section do not extend to next month. We conjecture that after negative overnight information shocks, new investors (the buyers) which bet on the potential gains do not behave like the individual investors do in standard *tug of war* case and this interplay between individual and institutional investors is broken. 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) which 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.

3.6. Stochastic Jump Dynamics

To advance our knowledge on non-deterministic jump dynamics, we take a profound look into positive and negative jump returns in an aggregate manner. As can be easily grabbed from the right-hand panels of Figure 1, value-weighted monthly positive and negative jump returns are almost mirror images of each other. With a careful watch, we can also notice a lagging pattern between these time series. This image serves as a visual representation of composite negative and positive jumps following each other. In Section 3.2, we also provided, overreaction and reversing mechanism between jump and non-jump returns.

To understand this dynamic nature and dependence between aggregated negative and positive jumps, we build a vector auto-regressive (VAR) model in the following general form.

$$
\begin{aligned}
\begin{pmatrix} PJ_t \\ NJ_t \end{pmatrix} = \begin{pmatrix} \alpha_{p0} \\ \alpha_{n0} \end{pmatrix} + \begin{pmatrix} \beta_{p1} & \beta_{p2} \\ \beta_{n1} & \beta_{n2} \end{pmatrix} \begin{pmatrix} PJ_{t-1} \\ NJ_{t-1} \end{pmatrix} + \begin{pmatrix} \beta_{p3} & \beta_{p4} \\ \beta_{n3} & \beta_{n4} \end{pmatrix} \begin{pmatrix} PJ_{t-2} \\ NJ_{t-2} \end{pmatrix} \\
+ \cdots + \begin{pmatrix} \beta_{p(2l-1)} & \beta_{p(2l)} \\ \beta_{n(2l-1)} & \beta_{n(2l)} \end{pmatrix} \begin{pmatrix} PJ_{t-l} \\ NJ_{t-l} \end{pmatrix} + \begin{pmatrix} u_{pt} \\ u_{nt} \end{pmatrix}
\end{aligned} \tag{14}
$$

where PJ_t and NJ_t are respectively the positive and negative monthly value weighted jump returns and l shows the lag number. To determine the lag-order, we mainly look at AIC for each VAR system in overnight, intraday and daily jump returns. That said, we also look at *partial auto-correlation functions (pacf)* of each time series to see the lags that have direct connection with the dependent variable. In each of the six time series, geometric decay in *pacfs* is quite fast after the first lag and other significant lags fluctuate nearby significance boundary. Even so, we conform to AIC lag-orders in our model construction and perform the generalized model in Eq. 14 and report results with corresponding lag-orders for each VAR system in Table 12.

Our VAR analysis shows bi-directional Granger-causality for negative and positive market jump returns. In line with our expectations, first lags of the jump returns in each day partition are statistically significant with the opposite signs. Although, overnight jump returns are modelled only with the first lags, lag-dependence is very extended for intraday and daily jump returns. We also see changing signs in higher lag orders and it becomes harder to grasp how the overall direction of the relationship between these variables will evolve. To comprehend that, we report the impulse responses in Figure 5. First step responses are all as expected. Inter-connectivity evolves very smoothly for overnight jumps. For intraday and daily sections, shocks from negative jumps do not disappear completely. 12-month forecast results are depicted in Figure 6.

Table 12 VAR Results for Composite Jump Returns

Table reports VAR results of value-weighted market jump returns for overnight, intraday and daily sections. Lag orders are selected via AIC numbers. We report absolute values of Newey-West t-statistic results for 12 lags in paranthesis.

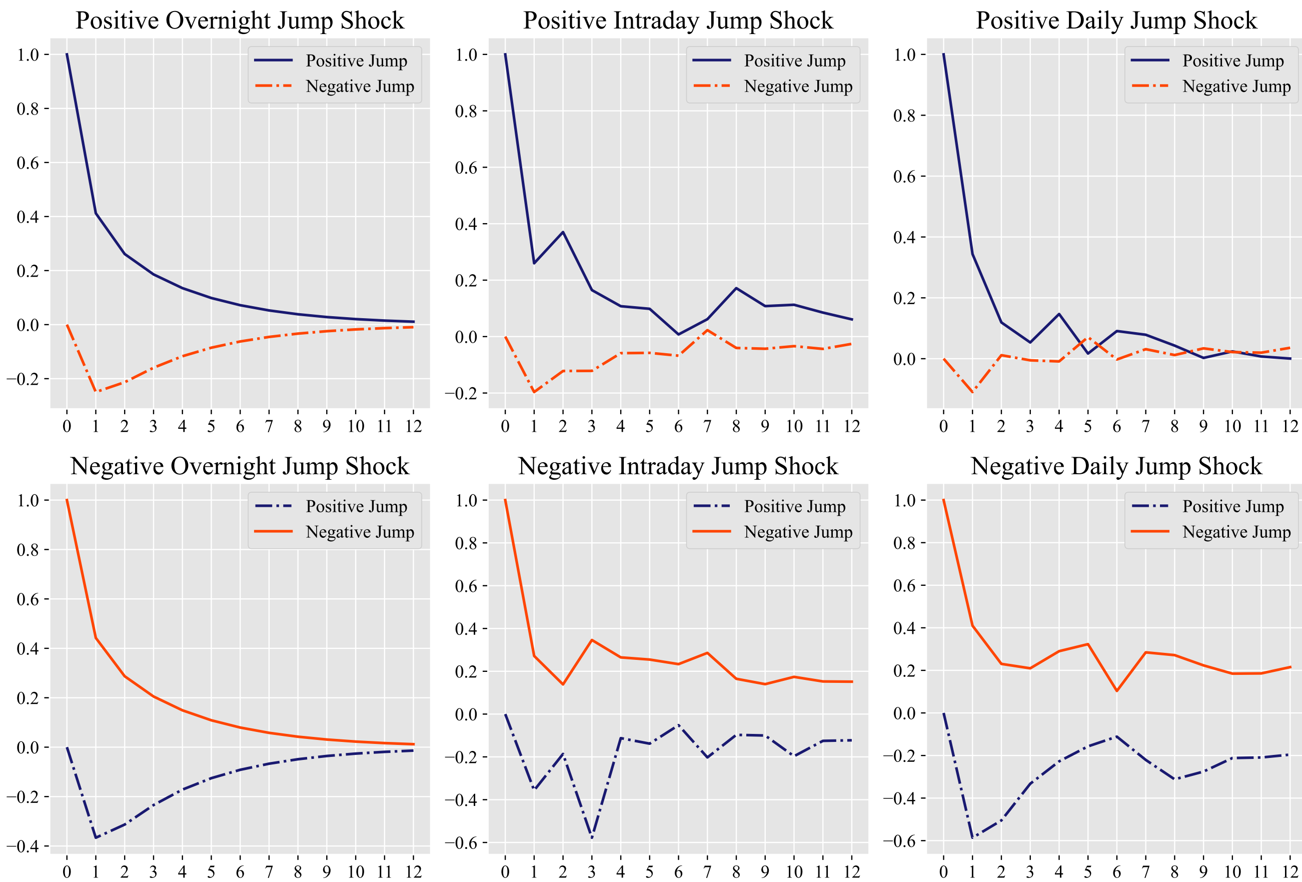
	PANEL A		**PANEL B**		**PANEL C**	
	Overnight Jumps		**Intraday Jumps**		**Daily Jumps**	
Dep. Variable	PJ_t		PJ_t		PJ_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	0.01	(3.86)*	0.02	(2.38)*	0.01	(0.91)
PJ_{t-1}	0.41	(6.29)*	0.26	(7.41)*	0.34	(4.93)*
NJ_{t-1}	-0.37	(2.95)*	-0.36	(2.81)*	-0.59	(2.02)*
PJ_{t-2}	-	-	0.23	(2.57)*	-0.06	(0.63)
NJ_{t-2}	-	-	0.00	(0.04)	-0.06	(0.67)
PJ_{t-3}	-	-	-0.03	(0.54)	0.03	(0.56)
NJ_{t-3}	-	-	-0.40	(2.18)*	-0.04	(0.31)
PJ_{t-4}	-	-	-0.13	(2.05)*	0.12	(1.51)
NJ_{t-4}	-	-	0.30	(2.18)*	0.03	(0.25)
PJ_{t-5}	-	-	0.07	(1.49)	-0.08	(1.79)
NJ_{t-5}	-	-	0.04	(0.45)	0.17	(1.85)
PJ_{t-6}	-	-	-0.03	(0.58)	0.16	(3.65)*
NJ_{t-6}	-	-	0.17	(1.09)	0.09	(0.89)
PJ_{t-7}	-	-	0.07	(0.84)	0.00	(0.03)
NJ_{t-7}	-	-	-0.20	(1.58)	-0.08	(0.82)
PJ_{t-8}	-	-	0.14	(3.48)*	-	-
NJ_{t-8}	-	-	0.15	(2.11)*	-	-
$Adj.R^2$	0.43		0.39		0.42	
Dep. Variable	NJ_t		NJ_t		NJ_t	
	coef.	**t**	**coef.**	**t**	**coef.**	**t**
Intercept	-0.02	(7.86)*	-0.01	(2.88)*	-0.02	(3.03)*
NJ_{t-1}	0.44	(6.69)*	0.27	(4.68)*	0.41	(5.54)*
PJ_{t-1}	-0.25	(5.17)*	-0.20	(7.27)*	-0.11	(3.45)*
NJ_{t-2}	-	-	-0.01	(0.12)	0.00	(0.04)
PJ_{t-2}	-	-	-0.02	(0.71)	0.09	(2.51)*
NJ_{t-3}	-	-	0.27	(5.02)*	0.12	(2.10)*
PJ_{t-3}	-	-	-0.01	(0.24)	-0.03	(1.24)
NJ_{t-4}	-	-	-0.02	(0.44)	0.15	(2.67)*
PJ_{t-4}	-	-	0.07	(1.13)	0.01	(0.22)
NJ_{t-5}	-	-	0.14	(2.78)*	0.11	(2.76)*
PJ_{t-5}	-	-	0.00	(0.09)	0.10	(3.57)*
NJ_{t-6}	-	-	0.01	(0.21)	-0.08	(1.18)
PJ_{t-6}	-	-	0.00	(0.16)	-0.07	(2.44)*
NJ_{t-7}	-	-	0.16	(2.52)*	0.19	(2.96)*
PJ_{t-7}	-	-	0.07	(1.56)	0.05	(2.05)*
NJ_{t-8}	-	-	-0.08	(1.45)	-	-
PJ_{t-8}	-	-	0.01	(0.15)	-	-
$Adj.R^2$	0.50		0.51		0.50	

4. Implications

Our study has some implications for our understanding of the market efficiency and for practitioners, especially the active portfolio managers, that look around some insight for the future.

First, there is still this ongoing debate on the concept for which the return predictability should be attributed to. Is this concept the risk premium that is associated with some factors or is it investors' behavioral biases flawing the rationality? Present study contributes to cross-sectional return predictability literature by elaborating on investors' overreaction to overnight information

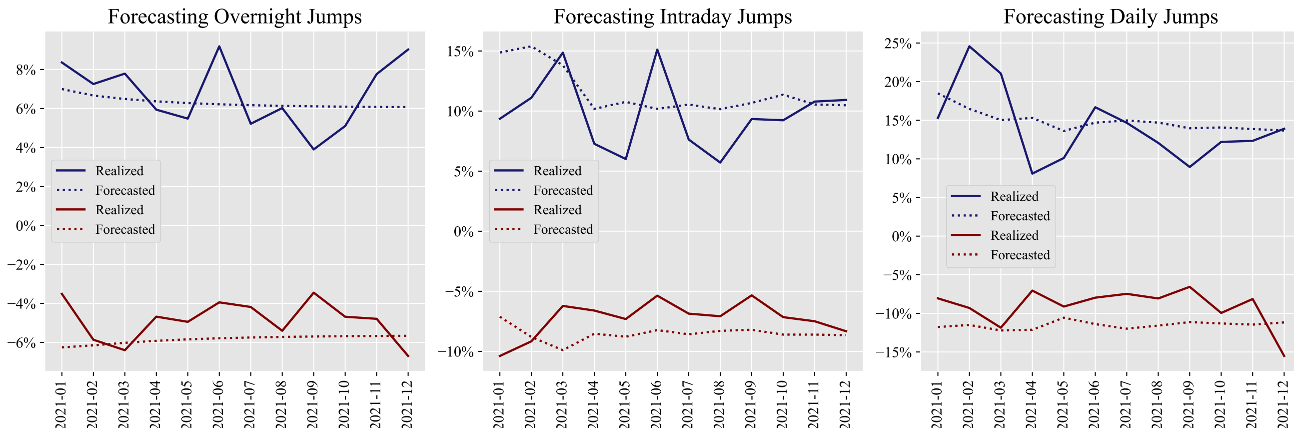
Figure 5: Impulse Responses for VAR



Notes: This graph shows percent of stocks in the market portfolio with jump reversal within the same and next month. We report results for overnight, intraday and daily sections.

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

Figure 6: Market Jump Forecasts for 12 Months



Notes: This graph shows the realized and forecast market jump returns for the whole months of 2021. Forecasts are reported for portion of the day.

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 which 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 because mainly of two reasons. First one is related with 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 to each other, we can expect this clientele effect 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 a positive news. All in all, we expect this return pattern to be persistent and open to exploitation by astute market participants that are free of psychological biases and vigilant for these opportunities. Just to be clear, our guess of long-lasting nature for this trend around overnight shocks are not tied to 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.

5. Conclusion

Investors' behavioral biases and its 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 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 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 statistically significant 0.8% of 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 insignificant for the lowest decile. Paper also documents that number of jump incidences are negatively correlated with prevailing conditional market volatility in almost every part of a day cycle. Negative intraday and daily jumps are also linked to market-wide liquidity conditions. By forming a composite jump returns separately for negative and positive cases, we also provide time-series predictability for aggregate negative and positive jump figures.

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

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