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Do idiosyncratic jumps matter?☆

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ABSTRACT

We show that idiosyncratic jumps are a key determinant of mean stock returns from both an ex post and ex ante perspective. Ex post, the entire annual average return of a typical stock accrues on the four days on which its price jumps. Ex ante, idiosyncratic jump risk earns a premium: a value-weighted weekly long-short portfolio that buys (sells) stocks with high (low) predicted jump probabilities earns annualized mean returns of 9.4% and four-factor alphas of 8.1%. This strategy's returns are larger when there are greater limits to arbitrage. These results are consistent with investor aversion to idiosyncratic jump risk.

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1. Introduction

Major firm-specific events often trigger large and abrupt changes or "jumps" in stock prices. Fama (1991) argues that rapid price changes around events are a feature of markets that efficiently incorporate new information. Although firm-specific jumps are often the result of important events, there is relatively little research on the effects of these jumps on mean stock returns.[1] This gap may be because classical asset pricing theory argues that firm-specific jumps can be diversified out in large portfolios and hence should not command a risk premium. In this paper, however, we show that firm-specific jumps are important determinants of the mean returns of a stock both from an ex post, as well as an ex ante, perspective.

We begin by examining the behavior of stock prices around jumps, which are days with absolute idiosyncratic returns greater than three conditional idiosyncratic standard deviations. One possible prior, motivated by the null hypothesis of event studies, is that idiosyncratic jumps have a zero mean and do not affect average returns. This prior predicts that mean abnormal returns are zero before, during, and after jumps. Instead, Panel A in Fig. 1 shows that cumulative abnormal returns relative to the Fama-French-Carhart (FFC) four-factor model are −2% over the 30 days before jumps. On jump days, stocks experience average abnormal returns of 2.5%, more than offsetting their prejump abnormal losses.

These return patterns around jumps are remarkably robust in the cross-section and the time series of individual stock returns. For example, they are present across NYSE size, bid-ask spread, Amihud illiquidity, and idiosyncratic volatility-based quintiles, and in the 1926–1963, 1964–1999, and 2000–2016 (post-decimalization) subsamples.

The fact that idiosyncratic jumps have positive means is surprising because jumps are defined symmetrically

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[1] Research that examines jumps or extreme individual firm returns includes Savor (2012); Jiang and Zhu (2016), and Jiang and Yao (2013). We discuss these papers in more detail below.

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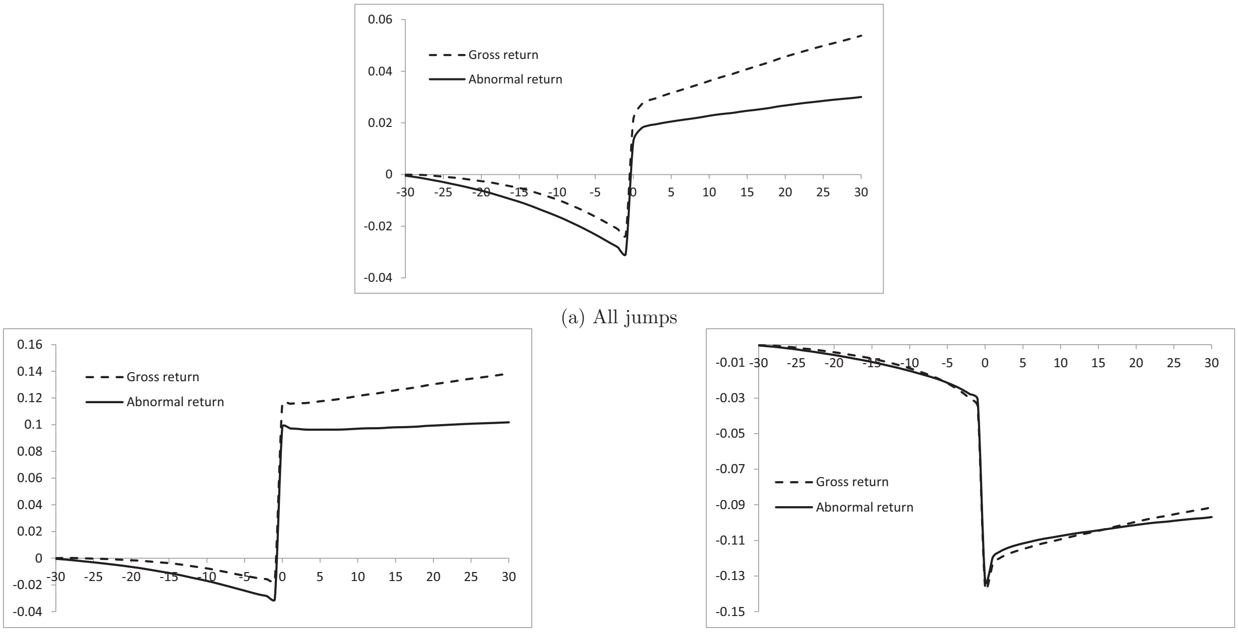


(a) All jumps

(b) Positive jumps

(c) Negative jumps

Fig. 1. The drift before jumps. The figure shows cumulative gross and abnormal returns over the 60-trading-day period surrounding jumps. A jump on date t is defined as an absolute daily idiosyncratic return in excess of three conditional standard deviations, where the return is idiosyncratic relative to the Fama-French-Carhart model, and the conditional standard deviation is based on an exponentially weighted moving average model. Abnormal returns are residuals over the (t–30, t+30) period from the Fama-French-Carhart model with loadings estimated over the (t–150, t–30) period. The figure displays the cumulative returns for all (Panel A), positive (Panel B), and negative (Panel C) jumps. The sample excludes stocks whose price is below \$5 at $t-31$ and the sample period is 1926–2016.

around zero. The mean is also large in economic terms: on average, the entire mean return of a typical stock accrues on the 4.5 days of the year that it experiences a jump. The mean return on the remaining 247.5 trading days of the year is zero. To put this another way, the entire average equal-weighted daily return of the stock market accrues from the 1.8% of stocks that experience a jump. The remaining 98.2% of stocks have a zero-mean return. Although the importance of jumps declines as firm size increases, more than half the value-weighted market return accrues from stocks that jump. Thus, jumps are a critical component of the mean return of an individual stock, as well as the market as a whole, in an ex post decomposition. Note that this decomposition does not imply that the entire equity premium is due to jumps. The net effect of "jump-related" price movements on mean stock returns is much smaller than the mean return on jump days, because of the negative returns before jumps.[2]

To identify the major causes of jumps, we merge our jump sample with Capital IQ's Key Developments database of news stories. We find that a significant fraction of the jumps we identify coincide with news stories. The most frequent news categories associated with jumps are announcements related to earnings, executive/board changes, clients, products, and mergers and acquisitions (M&A). One possibility is that the patterns we observe are specific to one of these categories and not due to jumps in general. In particular, starting with Beaver (1968), prior research finds that earnings announcements are associated with positive average returns, and hence our results may be a manifestation of the earnings announcements premium. In our sample, only 14% of jumps occur in the three-trading-day window around earnings announcements. The remaining 86% of jumps that are not related to earnings announcements also have positive jump-day returns on average. These results indicate that earnings announcements are not responsible for the jump-day returns.

What explains this pattern in stock prices around jumps? We consider three broad sets of hypotheses: aversion to idiosyncratic jump risk, systematic risk related to jumps, and compensated jumps with positive means.

The first hypothesis is that some investors are averse to idiosyncratic jump risk. These investors push prices down as jump probabilities increase prior to realized jumps. This behavior results in a decline in stock prices before jumps and a jump-risk premium that is realized on jump days. Merton (1987) shows that in the presence of frictions that inhibit full diversification, idiosyncratic risk earns a premium in equilibrium. Prior research finds that several sets of investors are not well diversified in practice. For example, managers often hold large stakes in their employers to align incentives, active mutual funds often hold concentrated portfolios (Kacperczyk et al., 2005), and retail investors are underdiversified (Barber and Odean, 2008). Firm-specific jumps are also likely to be salient events for stock market investors, with absolute returns

[2] The total abnormal return related to jumps is 0.5% (−2% prejump returns + 2.5% jump-day return) per jump, or at most 2.2% per year.

of approximately 10% in our sample. Thus, given their salience and magnitude, idiosyncratic jumps are a likely setting to find any effects of idiosyncratic risk aversion.

The second hypothesis is that jump days have greater systematic risk, resulting in positive expected jump-day returns. This could happen if our estimation procedure misclassifies some systematic jumps as idiosyncratic. Another possibility is that individual stock jumps provide information about the market as a whole, leading to a systematic risk premium (as in Savor and Wilson, 2016 and Patton and Verardo, 2012 for earnings announcements).

The final hypothesis is that our results are due to a data-generating process for stock returns with positive mean idiosyncratic jumps. Such a data-generating process could arise either because the fundamental news environment of a typical stock is positively skewed or because managers strategically disclose news. If positive mean jumps arrive randomly, then idiosyncratic returns on nonjump days have to be negative to ensure that expected idiosyncratic returns are zero. For example, a standard jump-diffusion process for a stock contains a "compensator," which is an instantaneous drift with the same expected return but opposite sign as the mean jump return. We show that a generalized jump diffusion model can be consistent with the patterns in returns around jumps under certain conditions.

We conduct several tests of these hypotheses. Our main tests focus on predicted jump-day returns because these can be identified ex ante and are therefore not susceptible to look-ahead biases. Results on the prejump returns are less conclusive since they require an ex post identification of jumps and are briefly discussed in Section 8.

The first test estimates whether the jump premium exists when jump risk is measured ex ante. The central premise of the compensator hypothesis is that jumps earn a zero premium, whereas the jump-risk aversion hypotheses predict a positive premium. For jump risk to be priced in the cross-section, investors must be aware ex ante that some stocks have higher jump probabilities than others. We therefore examine whether option markets reflect changes in jump probability prior to jumps. We find that the Bollerslev and Todorov (2011) measures of left- and right-tail jump probability, as well as option-implied volatility, increase before both positive and negative jumps but realized volatilities do not.

We use this insight to estimate the ex ante jump-risk premium. We first predict jumps out of sample using option-implied jump probabilities and the difference between realized and implied volatility. We rank all stocks into quintiles based on their out-of-sample predicted jump probabilities and test whether stocks with high ex ante jump probability earn high returns. We find that stocks in the top equal-weighted (value-weighted) predicted jump-probability portfolio earn annualized returns of 24.3% (24.2%) more than those in the bottom predicted jump-probability portfolio over the next day, 8.7% (9.4%) over the next week (after skipping a day), and 6.1% (6.2%) over the next month. FFC four-factor alphas are of similar magnitudes for these portfolios.

We further show that these abnormal returns are closely tied to jumps. First, the alphas are due to stocks within the portfolios that actually jump. Second, realized jumps that are a surprise, in the sense that ex ante jump probabilities were low before the jump, do not command a premium. Third, the alphas persist for as long as realized jump probabilities across the long and short portfolios are significantly different from each other (seven weeks for equal-weighted portfolios) and die out when the predictability of jumps diminishes.

The jump-risk premium is distinct from the result in Ang et al. (2006) that stocks with high idiosyncratic volatility earn low average returns. We find that the ex ante jump-risk premium is present across portfolios sorted on idiosyncratic volatility. Although our results are empirically distinct, a question remains: why do investors appear to overprice stocks with high idiosyncratic volatility but underprice stocks with high idiosyncratic jump risk? We find that the jump-risk premium represents returns to the risk of future jumps, whereas the low returns to stocks with high idiosyncratic volatility are related to past realizations of uncertainty. In particular, after controlling for idiosyncratic volatility, increases in predicted jump probability are associated with increases in future returns, idiosyncratic volatility, and jump incidence. On the other hand, high idiosyncratic volatility is associated with high past volatility and jump incidence. Furthermore, we find that the low returns to stocks with high idiosyncratic volatility are concentrated in the diffusive component of returns, while the high returns to high jump-probability stocks are due to the jump component.

Our next tests distinguish between idiosyncratic and systematic risk-based explanations. First, we use the jump-probability sorted portfolios to test whether the jumps we identify are indeed idiosyncratic. If the high ex ante jump-risk portfolio includes stocks with greater systematic jump risk, then these jumps will not be diversified out, leading to jumps in the portfolio returns. We find that both low and high jump-probability portfolios have about the same number of total jumps and cojumps with the market, suggesting that we are indeed sorting on idiosyncratic and not systematic jump probability. Second, we also test whether individual jumps provide information about aggregate market conditions, leading to greater systematic risk. Patton and Verardo (2012) show that stock betas increase by 0.16 on earnings announcement days. Although we find that betas are higher for high jump-probability stocks, the difference in beta is too small to explain the large premium that this portfolio earns. Similarly, Savor and Wilson (2016) show that earnings announcers are exposed to greater systematic cash flow risk. They find that earnings-announcers returns predict aggregate earnings growth. However, we find that the high jump-risk portfolio does not predict aggregate earnings growth, suggesting that the mechanism in Savor and Wilson (2016) does not apply in our context.

An idiosyncratic jump-risk premium is at odds with the standard portfolio theory argument that any idiosyncratic risk should not be priced because it can be diversified away in large portfolios. If stocks with high jump probabilities earn high returns, rational traders with deep pockets should buy portfolios of such stocks and earn high returns with little risk. We show that this arbitrage activity is not as easy to execute as it seems. In particular, we find that limits to arbitrage inhibit diversified investors from pursuing this strategy to its full extent.[3] First, even portfolios with a relatively large number of stocks that trade the jump-risk strategy are exposed to substantial idiosyncratic risk, which is an important limit to arbitrage (Pontiff, 2006). The risk-return trade-off, in terms of the information ratio for investing in the jump-risk trading strategy, is similar to the Sharpe ratio of the market. Thus, trading on jump risk is by no means a “free lunch.” Second, we find that the returns to trading stocks with high jump risk are highest in stocks with the highest trading costs measured using the Gibbs sampler approach used by Hasbrouck (2009). This suggests that costly to arbitrage mispricing, rather than systematic risk, is responsible for the jump-risk premium.

Our paper is closely related to research on the effect of extreme events on stock returns. Savor (2012) finds continuations after large absolute returns in the presence of information (i.e., an analyst report) and reversals in the absence of information. Jiang and Zhu (2016) find that markets underreact to information as proxied by jumps and find continuation in jump returns. Our results are distinct because we focus on expected and realized jump returns, as well as the events leading up to them, whereas these studies investigate returns after jumps. Jiang and Yao (2013) argue that jumps in individual stock returns are due to new information and not systematic risk; they find that size, liquidity, and to a large extent value effects are due to jump returns and not continuous returns. Our results complement (Jiang and Yao, 2013) by showing that expected jumps are priced in the cross-section of stocks. Our results are also consistent with those of Bali and Hovakimian (2009), who find that the difference between call and put implied volatilities predicts both jumps and high returns at the individual stock level. Yan (2011) develops a measure of expected jump size using option data and relates this measure to the returns of the underlying stock.

More generally, our paper is related to research that finds premiums associated with major news events. Savor and Wilson (2013) find that macroeconomic announcements are associated with positive average returns. Beaver (1968) and Barber et al. (2013) find that earnings announcements in the United States and across the world are also associated with positive average returns. Our results complement this literature by showing that idiosyncratic news is also associated with positive average returns, and that these high average returns exist even after excluding macroeconomic news and earnings announcements. Taken together, our results suggest that major news events, whether systematic or idiosyncratic, are associated with positive average returns. Average returns on days with news are large and on days with no news are small or even zero.

Our paper is also related to the large literature that analyzes whether jumps exist and what their impact is on systematic risk premiums and option prices. Barndorff-Nielsen and Shephard (2006), Lee and Mykland (2008), and Jiang and Oomen (2008) propose methods to identify jumps. Our measure of jumps is closest to the one proposed by Lee and Mykland (2008).

[3] We use the term arbitrage loosely, as is common in the literature. Profits are certainly not risk free as the technical definition of arbitrage requires.

2. Data and methodology

This section describes the data we use, our measure of jumps, and the methodology we use to estimate abnormal returns.

2.1. Data

Our primary sample consists of stocks in the Center for Research in Security Prices (CRSP) daily file with common shares outstanding (share code 10 or 11) from 1926 to 2016. On any given day t, we exclude stocks with a price less than \$5 as of day t–31 to mitigate potential microstructure biases in low-priced stocks. In the latter part of the paper we conduct tests using jump probabilities and implied volatilities extracted from option prices. For that analysis, we obtain data on option contracts from OptionMetrics. Our sample of option data is from January 1996 to April 2016. We apply standard filters on OptionMetrics data to ensure data quality.[4] We also use Compustat quarterly data to identify earnings announcement dates and the Capital IQ Key Developments database for other news events. These Compustat quarterly data are available from 1972 through 2016, and the Key Developments data are available from 1998 to 2015.

2.2. A measure of realized jumps

We use a simple measure of extreme price movements: a daily idiosyncratic stock return in excess of three conditional idiosyncratic standard deviations of that stock's returns. We define idiosyncratic returns as returns adjusted for exposure to the FFC factors. To compute FFC-adjusted returns for day t, we first estimate individual stock factor loadings by regressing returns on the FFC four factors on a 120-trading day rolling window from t–150 to t–31 for each stock:

$$r_{it} = \alpha_i + B_i * F_t + \epsilon_{it},$$

where r_{it} is the delisting-adjusted excess return on stock i, F_t is a vector of the FFC four factors, and α_i and B_i are stock-specific coefficients. The factor-loading estimates, $\hat{B}_{i,t}$, are used along with the realized values for the factor returns on day t to determine a predicted value for the stock return each day. The difference between the realized returns for the stock and the predicted values are the FFC-adjusted returns:

$$r^{idio}_{i,t} = r_{i,t} - \hat{B}_{i,t} * F_t. \tag{1}$$

Note that we include an intercept while estimating factor loadings but set it to zero when computing predicted

[4] We exclude index options (require $indexflag = 0$). We require common stock only ($issuetype = 0$), positive option volume, bid-ask restriction ($bid < ask$), and standard settlement contracts only ($ssflag = 0$). The contract must satisfy arbitrage bounds: for a put contract: $X \geq bid\,\&\,ask \geq \max(0, X - S)$; for a call contract: $S \geq bid\,\&\,ask \geq \max(0, S - X)$.

returns. To avoid the impact of outliers in the estimation, we winsorize the factor loadings at the 5% and 95% levels. We also use the r_{it}^{idio} series to measure the stock's conditional volatility, using an exponentially weighted moving average (EWMA) model. The conditional volatility for day t is based on the entire history of r_i^{idio}s up to date t–1:

$$\sigma_{i,t} = \sqrt{(1-\lambda)\sum_{s=1}^{t-1}\lambda^s (r_{i,t-s}^{idio})^2},$$

where λ=0.94, following RiskMetrics. We use the EWMA model, rather than a more sophisticated model such as generalized autoregressive conditional heteroskedasticity (GARCH), to eliminate the need for estimating firm-specific parameters on a rolling basis.

We categorize day t as a jump day for stock i by defining an indicator variable $J_{i,\,t}$:

$$J_{it} = \begin{cases} 1 & \text{if } \dfrac{|r_{i,t}^{idio}|}{\sigma_{i,t}} > 3, \\ 0 & \text{otherwise.} \end{cases}$$

This measure is similar in spirit to that of Lee and Mykland (2008), except that their measure uses bipower variation, rather than volatility, in the denominator and is based on total, rather than idiosyncratic, returns. Because bipower variation does not include volatility due to jumps, their measure typically classifies more events as jumps than our measure. We use standard deviation rather than bipower variation for simplicity; in the online Internet Appendix we show that our key results are robust to using bipower variation instead of standard deviation. In additional robustness analysis in the online Internet Appendix, we show that our key results are similar if we use other thresholds (2 and 4) to identify jumps, or if we analyze weekly as opposed to daily jumps.

2.3. Option-implied measures

We employ data on option contracts to build measures of implied volatility and jump probabilities.

- Call and Put Implied Volatility (IV): We use the measures of implied volatility for calls and puts provided by OptionMetrics for all stocks in our sample with available option data. For each underlying stock, we use the shortest maturity put and call contracts with a maturity of at least eight days. For each contract type (i.e., put or call), we use the contract that is closest to the money (i.e., moneyness of approximately one). We use the average implied volatility obtained from these put and call contracts as the stock's implied volatility.
- Left- and right-tail probabilities: We calculate the left-tail (LT) and right-tail (RT) jump measures derived from option data using the procedure of Bollerslev and Todorov (2011). The two measures reflect the intuition that the value of an out-of-the-money option contract with a short maturity is heavily influenced by the probability of a jump, since the probability of such contracts expiring in the money in the absence of jumps is very small. For LT (RT), we use the put (call) contracts with moneyness of 0.9 (1.1). To ensure comparability of LT and RT estimates across stocks, we use the implied volatility measure in the OptionMetrics database for each contract to interpolate the implied volatility of a contract with moneyness of exactly 0.9 (1.1). We need two contracts with moneyness around 0.9 for LT (1.1 for RT) to perform this interpolation. Using the interpolated IV value, we use the Black-Scholes formula to calculate the price of the contract. The LT (RT) measure is defined as the ratio of the price of this contract to the stock price adjusted for the contract's maturity. Specifically, if we assume that P is the price of a put contract with moneyness 0.9 and C is the price of a call with moneyness 1.1, then Bollerslev and Todorov (2011) define LT and RT as:

$$LT = \frac{e^{r\tau}P}{\tau S},$$

and

$$RT = \frac{e^{r\tau}C}{\tau S},$$

where r is the risk-free rate, τ is time to maturity (in years), and S is the underlying stock price.

2.4. Abnormal returns

We require measures of abnormal returns to test whether returns on jump days, as well as the 30 days preceding and following jumps, are unusual. We use two methods to measure abnormal returns: the FFC model and the Daniel et al. (1997) (hereafter DGTW) characteristics-based method. We use the FFC-adjusted series described in Eq. (1) as our measure of abnormal returns for stock i on day t. Note that these are computed based on factor loadings estimated using rolling windows from $t-150$ to $t-31$. Thus, factor-loading estimation does not intersect with the computation of abnormal returns over the 30-day prejump period.

We also apply the methodology of Daniel et al. (1997) at the daily frequency to compute DGTW-adjusted returns. We use the monthly portfolio assignment data from Russ Wermers's website to determine the characteristics-based match for firms in our sample. We combine the monthly portfolio assignment data with the CRSP daily return file to calculate daily DGTW portfolio returns. We compute the DGTW-adjusted return for each firm as the difference between the firm's realized return and the realized return for the matching portfolio.

2.5. Mid-quote returns

In a robustness test, we identify jumps and compute abnormal returns using returns calculated from the midpoint of closing bid and ask prices (and adding in dividends when applicable). We use bid and ask data from CRSP. The coverage of these data in CRSP is not comprehensive before 1993. Hence in this test, our sample is restricted to 1993–2016.[5]

[5] In unreported tests, we find similar results if we use all available bid-ask data from 1926 onward.

Table 1
Descriptive statistics.
Table 1 provides summary statistics for the key variables in this paper. The sample in this table consists of common stocks in the CRSP universe from January 1926 to December 2016, excluding stocks with price less than $5, 31 trading days prior to the observation. When available, the data set is augmented with OptionMetrics data on option contracts. We report statistics for four samples: all firm/day observations, only firm-days that are not jumps, only positive jumps, and only negative jumps. A jump is defined as a daily absolute idiosyncratic return in excess of three conditional standard deviations, where the return is idiosyncratic relative to the Fama-French-Carhart model, and the conditional standard deviation is from an exponentially weighted moving average model. *Return* is the raw daily return adjusted for delisting, *Size* is the market value of equity (in $ million), *Spread* is the difference between closing ask and bid prices, *Bipower volatility* is the annualized square root of conditional bipower variation (an exponentially weighted moving average of $|r_{i,t}||r_{i,t-1}|$ where r are daily returns), *Realized volatility* is the annualized exponentially weighted standard deviation of daily returns, *Implied volatility* is the Black-Scholes implied volatility of ATM option contracts, and *Right tail* (*Left tail*) is the option-implied positive (negative) jump probability proposed by Bolerslev and Todorov (2011).

	All			No jump			Positive jump			Negative jump		
	Mean	Std. dev.	N	Mean	Std. dev.	N	Mean	Std. dev.	N	Mean	Std. dev.	N
Return	0.06%	3.08%	54,784,534	0.01%	2.63%	53,807,188	9.22%	9.31%	607,327	−8.38%	6.97%	370,019
Size ($ million)	1638	10,654	54,730,732	1641	10,666	53,753,562	1336	9496	607,206	1609	10,678	369,964
Spread	0.4954	20.9855	30,525,754	0.4949	21.1561	30,005,190	0.5306	5.2204	312,902	0.5064	4.9235	207,662
Bipower vol.	30.46%	17.95%	53,675,341	30.49%	17.96%	52,741,113	29.12%	17.72%	584,363	27.89%	16.75%	349,865
Realized volatility	41.39%	25.23%	53,675,341	41.43%	25.26%	52,741,113	39.87%	24.23%	584,363	38.27%	22.39%	349,865
Implied vol.	42.65%	24.12%	6,672,128	42.57%	24.07%	6,573,792	47.87%	27.42%	55,655	47.24%	26.20%	42,681
Right tail	28.17%	28.69%	3,574,893	28.08%	28.53%	3,516,244	34.12%	36.86%	32,620	33.12%	35.76%	26,029
Left tail	23.53%	26.40%	4,054,462	23.45%	26.28%	3,992,080	28.50%	32.56%	34,498	28.87%	33.09%	27,884

2.6. Summary statistics

Table 1 provides summary statistics for the key variables in the paper for all days, as well as separately for no jump, positive jump, and negative jump days. The mean return on no jump days is 0.01%, as opposed to 0.06% for the full sample. This difference implies that jump days have positive average returns that constitute a large fraction of the average returns of a typical stock. The positive average returns of stocks on jump days are largely due to the fact that there are more positive jump days (1.11% of the sample) than negative jump days (0.68% of the sample). Returns are −8.38% on negative jump days and 9.22% on positive jump days. Overall, jump days are much more likely than predicted by the 3σ tail probabilities of the normal distribution. In unreported results, we find that the distribution of jumps is fairly concentrated around the mean: on average, 65% of firms experience between two and six jumps, and over 95% of firms experience seven jumps or fewer in a given calendar year.

The table also reports firm characteristics for the no-jump subsample. All characteristics (except the returns described above) are as of the day prior to the jump or no jump day. Stocks that will experience positive jumps over the next day are a little smaller than both stocks that will experience negative jumps and the full sample. Stocks that will experience both positive and negative jumps over the next day have higher call and put implied volatilities, as well as left- and right-tail jump probabilities, than stocks that do not experience jumps. This pattern suggests that the option markets reflect differences in jump probabilities. However, realized volatility and bipower variation are smaller for the jump sample as compared with the no jump sample. Thus, although markets anticipate greater future volatility for stocks that will experience jumps, these stocks do not have higher past realized volatility.

3. Stylized facts

This section presents a set of stylized empirical facts about returns in the 30 days before and after idiosyncratic jumps, the economic significance of jump-day returns, and the association of jumps with news and earnings announcements.

3.1. Returns around jumps

Fig. 1 examines stock returns over the 61-trading-day window $(t-30,\ t+30)$, where t is a jump day. Panel A presents results for all jumps, and Panels B and C examine positive and negative jumps separately. In each panel, the dashed line is the cumulative average gross return, whereas the solid line is the cumulative average abnormal return relative to the FFC model. As described in Section 2.4, we compute FFC-adjusted returns for any stock on any given day t using factor loadings estimated over $(t-150,\ t-31)$ and realized stock and factor returns on day t. We then compute average FFC-adjusted returns across all stocks for each day in event time, and compound the average to obtain cumulative abnormal returns (CARs) over the event window.

In Panel A, we see that prices drift down over the 30 trading days prior to jumps with a CAR of −1.9%. Then, in a single day, stocks more than recover the returns lost over the prior 30 days, with abnormal returns of 2.5% on the jump day. The large positive mean return is surprising, because jumps are defined symmetrically around zero, and this panel includes all positive and negative jump days. There is a small continuation on day $t+1$, and then CARs stay flat from $t+2$ onward. Panels B and C show that pre-jump returns are negative and of similar magnitude before both positive and negative jumps, suggesting that prejump returns are unlikely to be caused by information leakage about the direction of the eventual jump.

Table 2 presents statistical tests of the returns before, during, and after jumps. Panel A reports three measures of average stock returns in the 30-trading-day period $(t-30,\ t-1)$, where t is the day of the jump: gross returns, FFC-adjusted returns, and DGTW-adjusted returns. Gross returns are negative before both positive and negative jumps. On average, returns over the 30 trading days leading up to

Table 2
Returns around jump days.

Panel A reports average gross and abnormal returns over the period $t-30$:$t+30$ for all stocks that experience a jump on day t. A jump is a daily absolute idiosyncratic return greater than three conditional idiosyncratic standard deviations from an exponentially weighted moving average model. We compute $r_i^{adj} = r_i - r_i^p$ for all stocks each day in the t-30:t+30 window, where r_i is the realized stock return of stock i, and r_i^p is its predicted return. For gross returns, r_i^p is 0; for FFC-adjusted returns, it is the predicted return obtained from Fama-French-Carhart factor loadings estimated using regressions over $(t-150,\ t-31)$ and realized factor returns on that day; and for DGTW-adjusted returns, it is the return of the matching size/book-to-market/momentum portfolio on that day. The column $t-30$:$t-1$ reports the average of the cumulative return r^{adj} over $t-30$:$t-1$, the column t reports averages of r^{adj} on day t, and the column $t+1$:$t+30$ reports the average of the cumulative return r^{adj} over $t+1$:$t+30$. In Panel B, we form equal-weighted portfolios on day t that contain stocks that will experience a jump at some point in the interval t+1:t+30 (first column), on t (second column), and the interval t-30:t–1 (last column). The second and third sets of columns repeat the analysis with only positive and negative jumps, respectively. The panel reports results of daily calendar-time regressions of excess returns of these portfolios on the Fama-French-Carhart factors. Alphas for the $t-30$:$t-1$ and $t+1$:$t+30$ periods in Panel B are multiplied by 30 to be comparable to the corresponding numbers in Panel A. The sample excludes stocks whose price at $t-31$ is below \$5 over the period 1926–2016.

Panel A. Event time estimates

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Gross returns	−1.23%	2.55%	1.29%	−0.45%	9.22%	1.23%	−2.51%	−8.38%	1.38%
	(−4.23)	(25.69)	(4.91)	(−1.54)	(90.13)	(5.04)	(−8.63)	(−71.77)	(4.38)
FFC adjusted	−1.83%	2.51%	−0.05%	−1.63%	9.34%	−0.21%	−2.16%	−8.69%	0.21%
	(−28.44)	(33.05)	(−0.97)	(−20.88)	(74.27)	(−4.05)	(−29.44)	(−55.08)	(2.25)
DGTW adjusted	−2.14%	2.41%	−0.43%	−2.24%	8.95%	−0.64%	−1.98%	−8.32%	−0.10%
	(−30.24)	(28.12)	(−7.88)	(−27.17)	(81.38)	(−11.00)	(−17.65)	(−74.30)	(−1.08)

Panel B. Calendar-time estimates

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Alpha	−1.56%	2.91%	0.31%	−1.86%	8.54%	−0.39%	−1.53%	−7.56%	1.56%
	(−23.86)	(42.93)	(5.62)	(−22.19)	(93.31)	(−6.52)	(−20.18)	(−98.38)	(16.57)
Mkt – Rf	1.00	2.11	1.06	1.03	1.18	1.07	0.92	1.03	1.01
	(138.81)	(37.50)	(120.82)	(104.25)	(25.46)	(122.00)	(99.14)	(34.65)	(83.79)
SMB	0.55	1.57	0.51	0.60	0.77	0.55	0.49	0.60	0.46
	(26.54)	(11.43)	(25.67)	(26.70)	(6.24)	(29.29)	(23.41)	(10.16)	(17.41)
HML	0.23	0.17	0.23	0.24	0.18	0.25	0.19	0.27	0.19
	(19.05)	(2.11)	(18.83)	(15.92)	(2.53)	(20.73)	(12.88)	(4.11)	(9.67)
UMD	−0.05	−0.20	−0.04	−0.04	0.00	−0.02	−0.07	−0.20	−0.11
	(−4.11)	(−2.21)	(−3.62)	(−3.27)	(0.03)	(−1.82)	(−5.14)	(−4.04)	(−5.74)

a jump are −1.2%. Positive jumps are preceded by returns of −0.5%, while negative jumps are preceded by returns of −2.5%. After adjusting for exposure to the FFC factors, abnormal returns before both positive (−1.6%) and negative jumps (−2.2%) are negative and highly significant. Results are broadly similar for DGTW characteristic-adjusted returns, with average abnormal returns of −2.2% before positive jumps and −2.0% before negative jumps.

Jump-day returns are large and positive at 2.5%. Not surprisingly, adjusting for risk does not impact the returns on jump days because expected daily returns are negligible compared with jump-day returns. Returns on negative and positive jump days are similar in absolute magnitude at −8.4% and +9.2%. However, because positive jumps are more frequent than negative jumps, as seen in Table 1, average returns on jump days are positive.

There is also a reversal in FFC-adjusted returns after both positive and negative jumps. Positive jumps are followed by negative abnormal returns, and negative jumps are followed by positive abnormal returns. These results are consistent with Savor (2012), who also finds unconditional reversals after large returns. He finds that these reversals are concentrated in stocks without an analyst revision that coincides with the large return. We do not examine returns after jumps in detail because these are studied extensively in Savor (2012) and Jiang and Zhu (2016).[6]

Panel B reports abnormal returns from calendar-time regressions. We form portfolios that reflect the prejump, jump day, and postjump returns. For prejump returns, we form a portfolio on day t consisting of stocks that will experience a jump over $(t+1,\ t+30)$. Similarly the postjump portfolio consists of stocks that have experienced a jump over $(t-30,\ t-1)$. Finally, the jump-day portfolio consists of stocks that experience a jump on day t. For comparability to Panel A, the daily returns of the pre- and postjump portfolios are multiplied by 30, whereas the jump-day portfolio returns are not.

Note that the prejump and jump-day portfolios are clearly not tradable strategies; rather, they are statistical tools that provide a different perspective from the event study results in Panel A. In this analysis, each day, rather

[6] Jiang and Zhu (2016) find that stocks in the top decile of cumulative returns on jump days over the past one to three months earn positive subsequent returns. Our results are not directly comparable to theirs because we include all positive jumps and do not further sort within the set of positive jumps, nor do we cumulate past jump returns.

than each jump, is equally weighted, so jumps that cluster in time have relatively lower weights. We regress returns of this portfolio on the FFC factors. The results of this analysis are qualitatively similar to those in Panel A. The prejump portfolio alpha is –1.6% before all jumps, and the jump-day portfolio has an alpha of 2.9%. The alphas for the postpositive and postnegative jump portfolios reflect the same reversal observed in the prior panel with FFC-adjusted returns.

3.2. The economic significance of jump-day returns

The previous section finds that mean returns on jump days are 2.5%. A quick calculation shows that these returns are economically meaningful. Given that the empirical probability of a jump is 1.8% from Table 1, there are 4.5 jumps per year on average. Thus, average returns over only the 4.5 jump days in a year are 11.3%. This number is similar to the average annual excess return of a stock, suggesting that excess returns on the remaining 247.5 days are near zero. Thus, the entire average excess return of a stock seems to accrue on the relatively few jump days that occur in a year. To make this calculation more precise, we decompose the average return of a stock into components due to jumps and nonjumps (“diffusive” returns). In particular, we decompose the daily return of each individual stock i as follows:

$$r_{it} = r_{it}J_{it} + r_{it}(1 - J_{it},) \tag{2}$$

where J_{it} is an indicator variable that equals one if day t is a jump day for stock i. We denote the first term on the right-hand side as the jump return and the second term as the diffusive return. Note that this decomposition takes into account the fact that jumps are relatively unlikely; on any given day the first term is zero for most stocks (98.2% of stocks on average).

Panel A of Table 3 presents estimates of the mean of each component of this decomposition using its corresponding sample average (across all stocks and over all days in our sample). The mean stock return in our sample is 5.5 basis points (bps) per day, or 13.8% per year (annualizing by multiplying the daily average by 252). The component attributed to jumps is 4.6 bps per day, or 11.6% per year. The diffusive return component of 0.9 bps per day, or 2.2% per year, is not significantly different from zero. The table also shows that the dominance of jumps in determining mean returns remains when we decompose log (continuously compounded) returns instead of arithmetic returns. Similarly, the entire excess arithmetic return over the risk-free rate is due to jumps: the diffusive component is –0.8 bps per day (not statistically distinguishable from zero).

The table also presents a similar decomposition of FFC-adjusted returns. This decomposition shows that the jump premium is not due to exposure to the FFC factors. The average FFC-adjusted return for the jump component is 4.5 bps per day, or 11.4% per year, while the diffusive component is –3.5 bps per day, or –8.7% per year. It is worth noting that the negative diffusive return reflects the fact that the factor betas are primarily driven by the diffusive component of returns. Therefore, the betas are high, yet mean returns are nearly zero for the diffusive component. As a result, the factor-adjusted diffusive returns are negative.

In Panel B, we decompose market excess returns over the risk-free rate at time t into jump and diffusive components:

$$\sum_{i=1}^{N_t} w_{it}(r_{it} - rf_t) = \sum_{i=1}^{N_t} w_{it}(r_{it} - rf_t)J_{it} + \sum_{i=1}^{N_t} w_{it}(r_{it} - rf_t)(1 - J_{it}), \tag{3}$$

where N_t is the number of stocks in the sample at time t, rf_t is the risk-free rate, and the weights w_{it} are either equal or value weights. The first term on the right-hand side is the component due to jumps, and the second is the diffusive component. This decomposition provides a different perspective from the individual stock return decomposition in Panel A for three reasons. First, similar to the distinction between calendar-time and event time approaches, the market return decomposition weighs each day rather than each return equally. Second, this decomposition allows us to value-weight returns within a day, thereby enabling a decomposition of the value-weighted market excess return. Finally, we can perform a more stringent test of whether the jump-day premium is due to systematic factors using calendar-time regressions. The individual stock decomposition in Panel A uses factor loadings estimated over $(t-150,\ t-31)$ for each stock and hence will not take into account any differences in factor exposures between jump and nonjump days. Taking factor exposure into account may be important because Patton and Verardo (2012) find that market betas are higher on jump days than nonjump days. Note that a systematic risk-based explanation of the jump-day mean return is unlikely given the magnitudes involved. Average daily market returns are 5 basis points, and jump-day returns are 250 basis points; hence, market betas would need to be 50 on jump days for the capital asset pricing model (CAPM) to explain the mean jump-day return. Nevertheless, calendar-time regressions of the jump component on returns will reflect ex post factor loadings on jump days.

Panel B reports results of regressions of these portfolio returns on just an intercept, an intercept and the market, and an intercept and the FFC factors. Note that each component is itself a portfolio because it is a linear combination of excess returns. These portfolios are not tradable, since the jump decomposition uses ex post information.

The first specification shows that the jump component of value-weighted market excess returns is 1.5 bps per day, while the diffusive component is 1.4 bps. In CAPM and FFC specifications for value-weighted portfolios, the jump component has a relatively small exposure to the market (β) but earns a significantly positive daily α of 1.3 bps (3.3% annually). The diffusive component, on the other hand, has a market β close to 1 and earns an offsetting negative α of -1.3 bps.

Jumps are a larger component of equal-weighted market excess returns. Consistent with Panel A, the entire equal-weighted market excess return accrues on jump days; the mean for nonjump days is zero. In factor model

Table 3
A Decomposition of average stock returns.
The table decomposes average stock returns into diffusive and jump components. The jump return (JR) is the stock's return on jump days, and zero otherwise, and the diffusive return (DR) is the stock's return on days without a jump, and zero otherwise. For each stock, a jump is a daily absolute idiosyncratic return in excess of three conditional idiosyncratic standard deviations from an exponentially weighted moving average model. Panel A reports full sample average returns as well as average diffusive and jump returns. Returns are either gross returns, log returns, excess returns over the risk-free rate, or Fama-French-Carhart model adjusted returns. t-statistics are reported in parentheses and are clustered by calendar month. The last column reports the average incidence of jumps in the sample. Panel B reports a decomposition of market excess returns into portfolios that reflect jump and diffusive components. Each day, the Jump (Diffusive) portfolio is the equal- or value-weighted average of JR (DR). The panel reports the average excess return on each portfolio as well as the portfolio alphas using the CAPM and FFC-factor model. t-statistics (in parentheses) are based on Newey-West standard errors with a 30-day lag. The sample includes all common stocks from 1926 to 2016 with a stock price above \$5 as of 31 trading days before the observation.

Panel A. Daily return decomposition

Gross returns			Log returns			
Total	DR	JR	Total	DR	JR	Jump prob
0.055%	0.009%	0.046%	0.009%	−0.025%	0.034%	1.783%
(6.13)	(1.14)	(29.05)	(0.95)	(−3.10)	(20.56)	
Excess over risk-free			**FFC-adjusted returns**			
Total	DR	JR	Total	DR	JR	Jump prob
0.037%	−0.008%	0.046%	0.011%	−0.035%	0.045%	1.783%
(4.17)	(−1.04)	(28.83)	(7.58)	(−22.21)	(36.13)	

Panel B. Calendar-time portfolio return decomposition

	Value-weighted		Equal-weighted	
	Diffusive	Jump	Diffusive	Jump
Intercept	0.014%	0.015%	0.000%	0.044%
	(2.03)	(13.59)	(0.02)	(31.05)
Alpha	−0.013%	0.013%	−0.027%	0.041%
	(−12.60)	(13.21)	(−10.01)	(35.14)
Mkt − Rf	0.952	0.065	0.945	0.078
Alpha	−0.013%	0.013%	−0.033%	0.041%
	(−12.64)	(12.73)	(−19.20)	(36.13)
Mkt − Rf	0.948	0.065	0.963	0.082
SMB	−0.039	0.004	0.450	0.058
HML	0.002	−0.005	0.229	0.012
UMD	0.003	−0.002	−0.034	−0.008

regressions, jump and diffusive components have market exposures of nearly zero and one, respectively. The αs are larger in magnitude than in the value-weighted specification, with the jump α having the same magnitude as the excess return. Overall, these results show that a typical stock's return can be represented by a stochastic process with a zero-mean drift and rare positive mean idiosyncratic jumps.

3.3. The pervasiveness of return patterns around jumps

Table 4 shows that both the negative returns before jumps and positive mean jump-day returns are pervasive phenomena that persist despite changing the sample period or conditioning on stock characteristics. Panel A shows that both patterns are robust across three subsamples: 1926–1963, 1964–1999, and 2000–2016. We split the data in this manner to have two roughly equal subsamples followed by the postdecimalization sample. Panels B through E show that both patterns are also remarkably robust in the cross-section of stocks. Although the absolute magnitudes of the prejump and jump-day returns decline with size, both are economically and statistically significant even in the top NYSE quintile of stocks, where prejump returns are –1.0% and jump-day returns are 0.9%. Both patterns are present across idiosyncratic volatility quintiles as well as Amihud liquidity quintiles.

It is possible that the patterns in returns around jumps are a mechanical result of bid-ask bounce. In particular, a large positive return is more likely to be classified as a jump if the previous day's closing price was at the bid than if it was at the ask. Hence, a positive jump is more likely to be preceded by a negative return and a negative jump by a positive return. Because there are more positive jumps than negative jumps, we see negative prejump returns on average. However, this hypothesis only explains negative returns at $t-1$ before positive jumps. The existence of a negative drift before day $t-1$ and before negative jumps is inconsistent with bid-ask bounce being responsible for

Table 4
The pervasiveness of the drift and jump-day returns.

The table reports cumulative average abnormal returns in the period t-30:t+30 for all stocks that experience a jump on day *t*. A jump is a daily absolute idiosyncratic return greater than three conditional idiosyncratic standard deviations from an exponentially weighted moving average model. Each day in the $t-31{:}t+30$, window, we compute $r_i^{adj} = r_i - r_i^p$ for all stocks in event time, where r_i is the realized stock return of stock *i*, and r_i^p is its predicted return. The predicted return is obtained from Fama-French-Carhart factor loadings estimated using regressions over $(t-150,\ t-31)$ and realized factor returns on that day. The column t-30:t-1 reports the average of cumulative returns r^{adj} over $t-30{:}t-1$, the column t reports averages of r^{adj} on day t, and the column t+1:t+30 reports the average of cumulative returns r^{adj} over t+1:t+30. Panels A–E report these averages for different subsamples. Panel A uses time periods to define the subsamples, whereas Panels B–E use quintiles of firm characteristics to define the subsamples. Panel F identifies jumps and computes abnormal returns based on returns computed from the midpoint of closing bid-ask spreads. The samples excludes stocks whose price at $t-31$ is below \$5. The sample period for Panels B through E is 1926–2016, while it is 1993–2016 for Panel F.

Panel A. Different samples

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
1926 – 1962	−1.42%	2.85%	−0.23%	−1.73%	7.99%	−0.94%	−0.83%	−7.05%	1.14%
	(−16.65)	(24.83)	(−3.92)	(−14.22)	(38.87)	(−15.25)	(−9.55)	(−35.25)	(9.32)
1963–1999	−1.99%	2.76%	−0.05%	−1.44%	9.30%	−0.10%	−2.93%	−8.50%	0.03%
	(−29.11)	(25.23)	(−0.82)	(−17.62)	(55.01)	(−1.59)	(−41.60)	(−34.79)	(0.25)
2000–2016	−1.69%	1.81%	0.04%	−2.05%	10.20%	−0.07%	−1.19%	−9.72%	0.20%
	(−9.40)	(14.15)	(0.33)	(−9.10)	(41.13)	(−0.56)	(−7.45)	(−48.13)	(1.09)

Panel B. NYSE size quintiles

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Small	−2.10%	3.38%	0.06%	−1.70%	10.72%	0.00%	−2.81%	−9.56%	0.16%
	(−21.47)	(31.77)	(0.58)	(−15.34)	(96.06)	(−0.04)	(−27.33)	(−77.86)	(1.08)
2	−2.01%	2.35%	−0.20%	−1.88%	9.33%	−0.53%	−2.23%	−9.34%	0.34%
	(−27.41)	(29.85)	(−3.38)	(−21.53)	(79.58)	(−7.94)	(−22.93)	(−73.47)	(3.34)
3	−1.73%	1.95%	−0.10%	−1.70%	8.17%	−0.40%	−1.77%	−8.14%	0.39%
	(−23.60)	(26.86)	(−1.38)	(−18.76)	(70.04)	(−5.15)	(−20.56)	(−67.02)	(3.55)
4	−1.43%	1.46%	−0.15%	−1.47%	7.11%	−0.39%	−1.38%	−7.08%	0.22%
	(−19.56)	(21.25)	(−2.14)	(−15.41)	(64.67)	(−5.21)	(−16.51)	(−64.58)	(2.07)
Big	−0.97%	0.87%	0.06%	−1.01%	5.67%	−0.17%	−0.93%	−5.76%	0.37%
	(−17.55)	(15.36)	(1.13)	(−13.57)	(60.45)	(−2.92)	(−13.15)	(−60.39)	(4.37)

Panel C. Volatility quintiles

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Low	−0.63%	0.82%	0.58%	−0.28%	5.01%	0.87%	−1.09%	−4.91%	0.19%
	(−14.64)	(16.68)	(9.40)	(−5.84)	(69.30)	(12.76)	(−19.34)	(−63.15)	(2.27)
2	−1.34%	1.84%	0.31%	−1.06%	7.98%	0.14%	−1.79%	−7.99%	0.58%
	(−25.86)	(25.41)	(5.95)	(−17.69)	(84.86)	(2.63)	(−23.71)	(−63.40)	(5.75)
3	−2.25%	2.96%	−0.18%	−2.00%	10.68%	−0.41%	−2.69%	−10.91%	0.23%
	(−29.62)	(29.40)	(−2.53)	(−22.21)	(82.78)	(−5.56)	(−27.18)	(−58.19)	(1.70)
4	−3.73%	4.68%	−1.05%	−3.40%	13.92%	−1.44%	−4.39%	−14.31%	−0.26%
	(−20.95)	(32.91)	(−8.63)	(−17.30)	(73.81)	(−11.48)	(−23.86)	(−53.02)	(−1.27)
High	−5.04%	8.76%	−2.54%	−5.09%	20.56%	−3.34%	−4.91%	−19.24%	−0.64%
	(−12.31)	(36.15)	(−12.41)	(−10.82)	(47.20)	(−15.44)	(−12.55)	(−33.71)	(−2.08)

Panel D. Liquidity quintiles

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Most	−1.53%	1.15%	−0.02%	−1.46%	7.10%	−0.09%	−1.62%	−7.45%	0.09%
	(−21.96)	(18.42)	(−0.24)	(−16.80)	(65.32)	(−1.15)	(−20.45)	(−60.99)	(0.89)
2	−2.14%	2.07%	−0.34%	−2.06%	8.95%	−0.58%	−2.27%	−9.08%	0.06%
	(−31.03)	(26.95)	(−5.78)	(−25.36)	(75.84)	(−8.88)	(−23.68)	(−72.05)	(0.63)
3	−1.95%	2.84%	−0.15%	−1.78%	9.74%	−0.37%	−2.24%	−9.29%	0.23%
	(−23.96)	(30.83)	(−1.85)	(−18.73)	(87.13)	(−4.04)	(−21.77)	(−83.86)	(1.66)
4	−1.58%	3.62%	0.20%	−1.43%	10.22%	−0.09%	−1.88%	−9.07%	0.77%
	(−15.26)	(36.54)	(2.04)	(−12.61)	(103.06)	(−0.88)	(−15.10)	(−81.12)	(4.79)
Least	−1.62%	4.73%	0.27%	−1.88%	12.28%	−0.23%	−1.13%	−9.77%	1.24%
	(-11.98)	(39.30)	(2.14)	(-11.94)	(83.38)	(−1.66)	(−7.60)	(−73.68)	(6.81)

(*continued on next page*)

Table 4 (*continued*)

Panel E. Spread quintiles

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Small	−1.69%	1.39%	0.00%	−1.70%	8.68%	−0.07%	−1.67%	−8.74%	0.10%
	(−15.55)	(12.40)	(0.00)	(−11.24)	(41.42)	(−0.76)	(−16.41)	(−48.56)	(0.70)
2	−2.02%	1.93%	−0.04%	−1.96%	9.81%	−0.14%	−2.10%	−9.74%	0.09%
	(−19.37)	(18.48)	(−0.51)	(−15.44)	(65.40)	(−1.49)	(−17.96)	(−73.84)	(0.61)
3	−2.16%	2.50%	−0.09%	−2.13%	10.90%	−0.16%	−2.21%	−10.56%	0.03%
	(−19.42)	(23.93)	(−0.89)	(−15.94)	(84.54)	(−1.57)	(−16.41)	(−94.83)	(0.21)
4	−2.35%	3.19%	−0.01%	−2.44%	11.74%	−0.06%	−2.21%	−10.64%	0.07%
	(−15.62)	(27.59)	(−0.06)	(−14.29)	(81.92)	(−0.42)	(−13.42)	(−86.99)	(0.38)
Large	−2.68%	4.49%	−0.06%	−3.69%	14.48%	−0.51%	−1.07%	−11.51%	0.64%
	(−14.98)	(29.43)	(−0.37)	(−15.99)	(57.88)	(−2.82)	(−5.90)	(−61.89)	(2.71)

Panel F. Mid-quote returns

	All jumps			Positive jumps			Negative jumps		
	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30	t-30:t-1	t	t+1:t+30
Midpoint	−2.30%	1.96%	−0.38%	−2.22%	9.69%	−0.47%	−2.41%	−9.28%	−0.24%
FFC adj.	(−17.01)	(17.30)	(−3.77)	(−13.96)	(58.68)	(−4.74)	(−16.77)	(−71.05)	(−1.54)

our results. Nevertheless, we conduct two tests to examine this question.

First, we sort stocks into quintiles based on their percentage bid-ask spreads (spread as a fraction of price). In the top spread quintile, the drift is larger in absolute magnitude before positive (−3.7%) as compared with negative jumps (−1.1%), consistent with the bid-ask bounce hypothesis discussed above. However, we find negative prejump returns and positive jump-day returns in all quintiles. Even in the quintile with the smallest spreads, magnitudes are only a little smaller relative to the full sample. These results suggest that bid-ask spreads are unlikely to be responsible for the patterns we observe around jumps.

Second, we repeat the analysis (including jump identification) using returns computed from the midpoint of the bid-ask spread. These mid-quote returns are immune to the bid-ask bounce critique discussed above. The sample for this analysis is 1993–2016, because coverage of bid-ask quotes in CRSP is not comprehensive before 1993. Panel F shows that the magnitudes of the prejump and jump-day returns do not change substantially when we use mid-quotes, confirming that bid-ask bounce is not responsible for our results.

Overall, for all of these characteristic-sorted samples, the magnitudes of mean prejump returns and jump-day returns appear to be related to the absolute magnitude of the jump. For example, as you move from the lowest to the highest idiosyncratic volatility quintile, the absolute return threshold to qualify as a jump increases. Along with this increase, prejump returns become more negative, and mean jump-day returns become more positive. We analyze this relationship more formally in the online Internet Appendix.

The result that jump-day returns are as large as the equity premium does not imply that there is no compensation for systematic risk. Because jumps are preceded by negative returns, the net effect of jumps is the sum of these negative returns and the positive jump-day return. Consider a simple thought experiment about the effect on returns of eliminating jumps. If we eliminate jumps, it naturally implies that we should also remove the negative returns that precede these jumps. The net effect of jumps is then at most 2.4% per year, which is about a quarter of the average excess return of a stock in our sample.

3.4. Information and jumps

What causes jumps in stock prices? It seems likely that large daily absolute returns for firms are related to important news. In this section, we examine whether the jumps we identify overlap with significant events for the affected firms and present the major categories of news associated with jumps. We use Capital IQ's News and Key Developments database to identify news events and match them to our sample of jumps. In particular, we match a jump to news if there is a news story in the three-trading-day window around the jump. We also restrict our sample to firms that have had at least one news story in the past calendar year to mitigate the impact of any differences in news coverage across stocks in our sample.[7] Table 5 shows the most frequent categories of news events associated with jumps. By far, the most frequent category of news is earnings announcements. These are followed by executive changes, client announcements, product announcements, and mergers and acquisitions (M&A) announcements.

Panel B shows that over the sample of stocks for which we have news coverage, 8% of stock days are associated with news; however, 40% of jump days are associated with news. The positive jump-day premium and negative prejump returns are present in both the news and nonnews subsamples; however, the absolute magnitudes are lower for the news sample.[8]

[7] We cannot distinguish between whether the news event causes the jump or whether journalists ex post write articles to rationalize jumps in stock prices. However, some of the news categories (e.g., earnings announcements) are clearly observable events and are likely to impact stock prices.

[8] The jump-day premium remains large (0.75% as opposed to 1.25% in the full sample) when we exclude the event type with the largest pre-

Table 5
Jumps and news events.
The table reports results on the association of jumps with news events. We match a jump to a news event if the jump occurs in the three-trading-day window centered on the news event date. Panel A reports the ten most frequent categories of news that correspond to jumps in returns. Panel B reports returns around jump days for two samples: daily stock returns that do not correspond to a news event and those that correspond to a news event. Panel C focuses on the relation between jumps and earnings announcements. We match a jump to an earnings announcement if the jump occurs in the three-trading-day window centered on the announcement date. We report average returns for all jump days, jump days matched with earnings announcement dates, and jump days not matched with earnings announcements over the sample period in which earnings announcements dates are available. The sample period in Panels A and B is January 1998 to December 2015 and for Panel C is January 1972 to December 2016. News events are identified using the Capital IQ Key Developments database, and earnings announcements are identified using the Compustat quarterly file. Standard errors are clustered by calendar month.

Panel A. Most common news event types

Event type	N
Announcements of earnings	47,467
Executive/Board changes — other	6425
Client announcements	6212
Product-related announcements	5645
M&A transaction announcements	4774
Earnings calls	4735
Corporate guidance — raised	4126
Conference presentation calls	3803
Corporate guidance — new/confirmed	2930
Corporate guidance — lowered	2722

Panel B. Returns around news events

	All jumps				Positive jumps				Negative jumps			
	t-30:t-1	t	t+1:t+30	N	t-30:t-1	t	t+1:t+30	N	t-30:t-1	t	t+1:t+30	N
No news days:	−2.38%	2.31%	−0.09%	146,322	−2.73%	10.31%	−0.33%	87,483	−1.85%	−9.59%	0.27%	58,839
	(−11.96)	(15.14)	(−0.63)		(−10.96)	(35.93)	(−2.39)		(−9.23)	(−36.85)	(1.20)	
News days:	−1.14%	1.25%	0.09%	98,908	−1.22%	10.33%	0.40%	55,525	−1.03%	−10.38%	−0.29%	43,383
	(−9.28)	(12.36)	(1.11)		(−8.96)	(67.53)	(4.13)		(−7.82)	(−54.07)	(−2.23)	

Panel C. Earnings jumps and nonearnings jumps

	All jumps				Positive jumps				Negative jumps			
	t-30:t-1	t	t+1:t+30	N	t-30:t-1	t	t+1:t+30	N	t-30:t-1	t	t+1:t+30	N
Full sample	−1.90%	2.34%	0.02%	775,666	−1.59%	9.69%	0.01%	471,915	−2.39%	−9.07%	0.03%	303,751
	(−24.13)	(26.12)	(0.27)		(−16.36)	(62.93)	(0.10)		(−28.05)	(−49.14)	(0.30)	
No earnings	−2.01%	2.59%	−0.02%	665,276	−1.63%	9.63%	−0.14%	410,805	−2.63%	−8.77%	0.17%	254,471
	(−24.45)	(26.63)	(−0.33)		(−15.95)	(57.70)	(−2.06)		(−30.54)	(−41.63)	(1.32)	
Earnings	−1.23%	0.84%	0.26%	110,390	−1.29%	10.10%	1.00%	61,110	−1.15%	−10.63%	−0.66%	49,280
	(−13.90)	(10.77)	(3.67)		(−12.66)	(81.90)	(11.44)		(−11.45)	(−70.71)	(−5.91)	

It is possible that the jump risk premium is driven by earnings announcements, because they are known to have positive mean returns (Beaver, 1968) and are the most frequent category of news in our sample. To test the robustness of the jump-day premium to excluding earnings announcements, we compare the jump-day premium for earnings-related jumps to all other jumps. In particular, we designate any jumps in the three-trading-day window around the quarterly earnings announcement date in Compustat (*RDQ*) as earnings-related jumps.

Panel C of Table 5 shows that only 14% of jumps are earnings related. The panel shows that mean jump-day returns are 2.6% for nonearnings jumps, as opposed to 0.8% for earnings jumps.[9] These results suggest that although there are some differences between jumps on earnings announcement dates and jumps on other dates, our results on the positive mean jump-day returns are not solely due to earnings announcements. In fact, mean returns on jump days are higher for nonannouncers compared with announcers.

The table shows that returns are negative before both positive (−1.3%) and negative (−1.2%) jumps on earnings announcement dates. The negative returns before positive jumps may appear surprising because prior research documents a pre-event drift in the direction of earnings surprises, presumably due to a leakage of information (Bernard and Thomas, 1990). This apparent contradiction is resolved by noting that we focus on events that are a surprise to markets as evidenced by stock price jumps, while earnings surprises are measured relative to earnings expectations. Announcements with a pre-event drift in the direction of the earnings surprise are less likely to be accompanied by jumps in prices on announcement

mium, M&A transaction announcements. In fact, 18 of the 20 most frequent news categories in our sample have positive abnormal jump-day returns.

[9] In unreported results, we use a matched sample of earnings and nonearnings jumps to control for any differences in the size and timing of earnings jumps relative to other jumps. After matching, the jump-day returns for earnings-related jumps are closer in magnitude to nonearnings jumps.

dates because some of that information has already been incorporated into prices. It is interesting to note that the figure in Bernard and Thomas (1990) that shows the preannouncement drift is a reproduction of Panel A of Fig. 1 in Foster et al. (1984) in which surprises are defined relative to earnings expectations. Panel C of Fig. 1 in Foster et al. (1984) defines surprises based on market returns. Panel A shows a drift in the direction of the earnings surprise, while Panel C shows a negative drift for both extreme positive and negative surprises defined based on returns. In unreported results we replicate all panels of Fig. 1 in Foster et al. (1984) and find the same pattern in Panel C over our much larger sample.

4. Possible explanations

As discussed in the introduction, we investigate three possible explanations for the pattern in returns around jumps: idiosyncratic jump-risk aversion, systematic components to jump returns, and a "compensator" for positive average jump returns.

4.1. Idiosyncratic jump-risk aversion

A possible explanation for our results is that some investors are averse to idiosyncratic jump risk, leading to an ex ante premium. A premium for idiosyncratic risk can arise if investors are underdiversified (Merton, 1987) or if they engage in narrow framing (Barberis and Huang, 2001). A crucial requirement for this hypothesis to explain the patterns that we observe around jumps is that investors can perceive that some stocks have higher ex ante jump probabilities than others. The positive mean return on jump days is at least in part compensation for bearing idiosyncratic jump risk.

This hypothesis can also explain the negative returns before jumps. If average jump probabilities increase in the 30-day period before realized jumps, jump risk-averse investors push prices down as average jump probabilities increase. This condition is likely to be satisfied empirically, because stocks whose jump probabilities have increased in the recent past are more likely to jump than those whose probabilities have decreased. Note that we do not expect negative returns to gradually accrue for a given stock. It is possible that for any given stock, the entire negative return accrues on a single day when new information arrives that implies a large increase in jump likelihoods. If these days are relatively evenly distributed across the prejump period, we will observe a negative drift in the sample average.

To summarize, this hypothesis requires that investors are aware of the prospect of jumps before jumps are realized, jump probabilities increase on average over the prejump period for stocks that jump, stocks with high expected jump probabilities earn positive abnormal returns, and limits to arbitrage prevent other well-diversified investors from arbitraging these positive returns away.

4.2. Jumps are associated with systematic risk

Back (1991) shows under a general rational model that only stock jumps that coincide with jumps in the stochastic discount factor should earn a premium. Although we try to exclude systematic jumps by identifying jumps in idiosyncratic returns relative to FFC factors, it is possible that the factor model is misspecified, and hence some of the jumps we identify are actually systematic. If this is true, the risk associated with these jumps could be related to systematic jump risk, thereby resulting in the jump-risk premium.

Another possible explanation is based on prior work on the earnings announcement premium by Patton and Verardo (2012) and Savor and Wilson (2016). These papers show that announcements by individual firms carry information about aggregate market conditions. Due to this information content, earnings announcements have a large systematic component justifying their premium. A similar mechanism can be responsible for the jump premium as well.

Both idiosyncratic and systematic risk hypotheses predict a decline in prices if jump probabilities increase before realized jumps. This is true even for earnings announcements when the date of a potential jump is known. Note that only a fraction of earnings announcements contain large surprises relative to expectations and hence result in jumps. We expect earnings announcements that coincide with jumps to be preceded by increases in jump probability on average, resulting in negative prejump and positive jump-day returns. In these cases, the decline in prices should occur as soon as there is information that jump probabilities have increased, rather than just prior to the announcement. If prices were to only decline immediately before the jump, then market participants could realize riskless profits by short selling the stock and closing their positions immediately before the announcement.

4.3. Compensator

The compensator hypothesis explains the positive mean returns on jump days without a systematic or idiosyncratic jump risk premium. The compensator hypothesis assumes that jumps with positive means are an exogenously specified feature of the data-generating process for individual stock returns. This could be because the news process of the underlying business of a typical firm has positive mean jumps. For example, a firm with a lot of real options, such as an oil exploration firm, could have positively skewed news. Or it could be that the underlying news process is symmetric, but managers disclose bad news strategically, releasing it slowly over time rather than at one go, while they release good news as it comes.

Under this hypothesis, unconditional mean idiosyncratic returns are zero because positive mean returns on jump days are "compensated" by negative mean returns on nonjump days. To illustrate this hypothesis, consider the stochastic differential equation for a stock price 'S' described in Merton (1976):

$$\frac{dS}{S} = \mu dt + \sigma dB + (dN - \lambda \delta dt), \tag{4}$$

where dB and dN are Brownian diffusion and Poisson jump processes respectively, μ is the expected instantaneous return due to systematic risk, λ is the jump intensity, and

δ is the mean jump return. Note that the last term $(dN - \lambda\delta dt)$ represents the compensated jump process and has a zero expected value. Thus, expected stock returns are determined solely by the systematic risk premium μ. However, the jump return can have a positive mean ($\delta > 0$), and the mean nonjump return ($\mu - \lambda\delta$) can be zero (as in the data) if $\mu = \lambda\delta$.

The compensated Poisson jump process outlined above cannot explain the negative returns before jumps because the memoryless property of the Poisson process implies that conditioning on a jump does not affect expected returns before or after jumps. We show in the appendix that a generalized version of this model can explain the negative returns before jumps if jumps are negatively serially correlated.

5. The ex ante jump-risk premium

In this section, we distinguish between the compensator and the two risk-based explanations for our results. In particular, we test whether stocks with ex ante high jump probability earn abnormal returns. The compensator predicts zero expected abnormal returns for such stocks, whereas the risk-based hypotheses predict positive expected abnormal returns. For the risk aversion hypotheses to explain the patterns around jumps, investors must be able to perceive that some stocks have higher jump probabilities than others and push their prices down leading to higher expected returns. In the first section, we test whether investor expectations of jump probabilities extracted from option markets increase before realized jumps. We use these insights to build a jump prediction model, test whether the model predicts jumps out of sample, and finally test whether portfolios constructed from sorts on ex ante jump probability have high returns.

5.1. Investor expectations of jump probabilities prior to jumps

To assess investor awareness of the likelihood of jumps, we use option data to derive measures of jump probability. Each panel in Fig. 2 presents two event time plots of average measures related to jump likelihood: one for positive events (+) and one for negative events (−). Panel A shows that historical realized volatility is relatively flat, or even downward-sloping, leading up to a jump. Panel B shows that at-the-money (ATM) option-implied volatility increases significantly in the days leading up to a jump. The forward-looking nature of implied volatility indicates that investors are aware of the likelihood of a jump. These charts suggest that the difference between implied and realized volatility may predict jumps. We test if this is the case later in the paper.

Panels C and D show that both left-tail (LT) and right-tail (RT) option-implied jump probabilities constructed as in Bollerslev and Todorov (2011) increase significantly prior to the event day and fall thereafter. These measures of jump probability support the premise that investors are, on average, aware of the high likelihood of an extreme event for firms that experience jumps, and that market expectations of jump probabilities increase prior to jumps. Note that both tail measures increase before both positive and negative jumps. This suggests that investors are aware of an increase in jump probability but have little information about the direction of the jump.

Table 6
Predicting jumps.
The table provides parameter estimates for a logistic jump prediction model where the dependent variable is an indicator variable that takes the value one if a stock experiences an idiosyncratic jump on day *t*. The predictor variables are *Tail* and *Volatility ratio* calculated at the end of the previous trading day. *Tail* is the average of the left-tail and right-tail measures of Bollerslev and Todorov (2011), and *volatility ratio* is the log difference of ATM option-implied volatility and the exponentially weighted standard deviation of past idiosyncratic returns. The sample consists of all stocks (for which variables are available on any day) from January 1996 to April 2016, excluding all stocks whose price 30 trading days before the observation was below \$5.

	Coefficient	Standard error	Odds ratio
Intercept	−5.037	0.009	
Tail	0.201	0.013	1.223
Vol. ratio	2.306	0.014	10.034
R^2	1.03%		

5.2. Predicting jumps

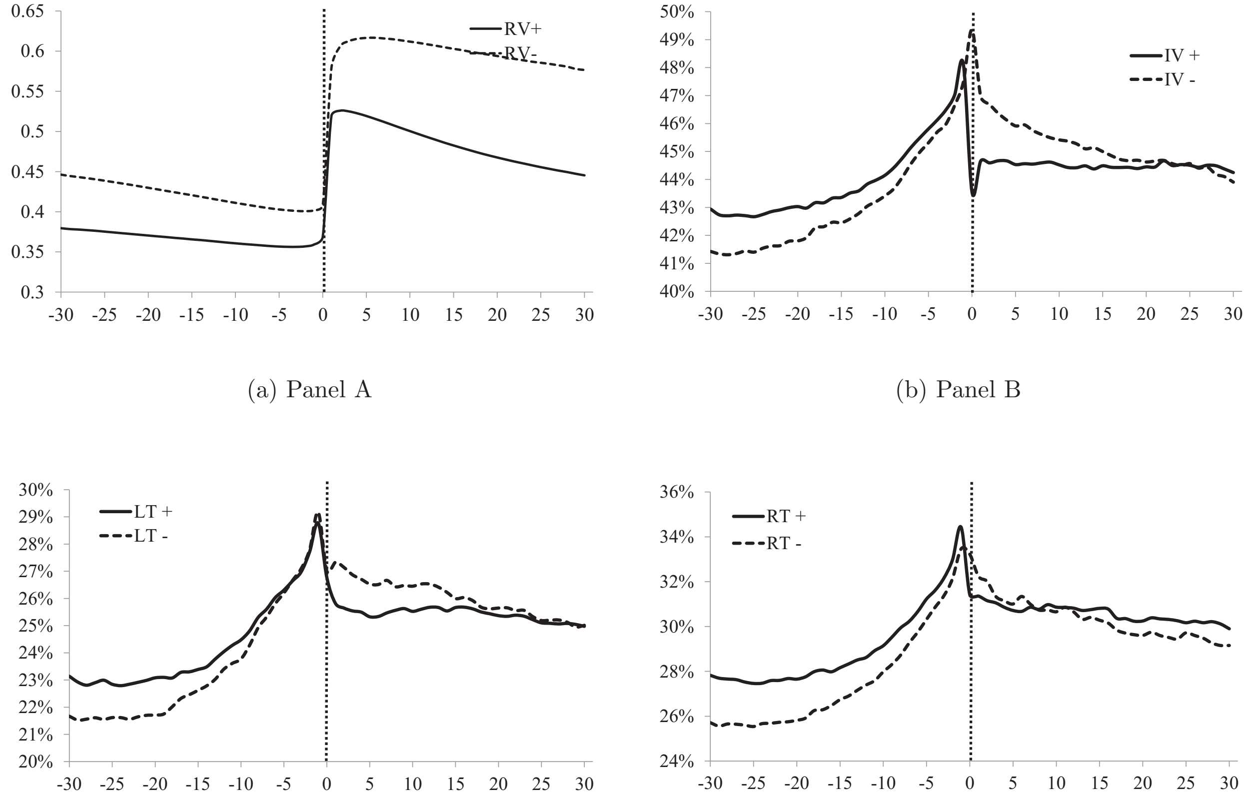
We develop a simple jump prediction model using two forward-looking variables extracted from option prices: average tail probability and the log ratio of option-implied volatility to conditional realized idiosyncratic volatility. Average tail probability is the average of the Bollerslev and Todorov (2011) left- and right-tail probability measures, LT and RT, defined above. We use the ratio of implied to realized volatility because Fig. 2 shows that implied volatility increases before jumps, while realized volatility stays the same. We use the average of LT and RT, rather than LT and RT separately, because we are interested in predicting jumps when there is information regarding the likelihood of a jump but not its direction. In such cases, both LT and RT will be high.[10] We use these variables as of day *t* to predict a binary jump indicator variable (that is 1 if a jump occurs on day *t*+1 and 0 otherwise) in a logit model.

Table 6 shows the estimated coefficients from this model over the full options sample. Both variables are significant in predicting jumps, with jump probabilities more sensitive to changes in the volatility ratio than tail probability, possibly because volatilities are measured more accurately. In the next section, we show that when implemented using an expanding window approach, this model succeeds in predicting jumps out of sample as well.

5.3. Jump-risk portfolios

In this section, we employ an out-of-sample version of the predictive regression in Table 6 to form portfolios based on ex ante estimates of jump probabilities. The

[10] We have also estimated a model with all four variables as predictors. This unrestricted model results in a greater spread in returns across the low and high jump probability portfolios. However, we use the restricted model in our main tests to allay concerns about capturing information from option markets on the direction of the jumps. Both models perform about equally in predicting jumps out of sample.



(a) Panel A

(b) Panel B

(c) Panel C

(d) Panel D

Fig. 2. Are investors aware of the likelihood of jumps? The figure displays conditional realized volatility (*RV*), implied volatility (*IV*), left-tail (*LT*), and right-tail (*RT*) probability over the 30 days before and after jumps. A jump on date *t* is defined as an absolute daily idiosyncratic return in excess of three conditional standard deviations, where the return is idiosyncratic relative to the Fama-French-Carhart model, and the conditional standard deviation is based on an exponentially weighted moving average model. Tail probabilities are extracted from option prices using the method of Bollerslev and Todorov (2011). Panel A displays realized volatility from an exponentially weighted moving average model before positive (RV+) and negative (*RV*−) jumps. Panel B displays implied volatility around negative jumps of the closest to money put (*IV*−) and the implied volatility around positive jumps of the closest to money call (*IV*+). Panel C displays left-tail probabilities around positive jumps (*LT*+) and negative jumps (*LT*−). Panel D displays right-tail probabilities before positive (*RT*+) and negative (*RT*−) jumps. The sample excludes stocks whose price is below $5 at $t-31$ and the sample period is January 1996 to April 2016.

associated trading strategy consists of holding stocks with high jump probabilities and selling stocks with low jump probabilities. To ensure that there is no look-ahead bias and the strategy can be implemented in real time, we use only available data as of time t to form portfolios held at time $t+1$. In particular, for any period t, we estimate the jump prediction model using an expanding window of data that ends at the end of the month immediately prior to the start of t. We then use current values of average tail probability and realized and implied volatility to generate out-of-sample estimates of predicted jump probability.

Table 7 reports the FFC factor regressions of five portfolios constructed from quintile sorts on these out-of-sample predicted jump probabilities. Panel A presents results for returns over the next day. The equal-weighted portfolio of the lowest jump probability stocks earns annualized (by multiplying by 252) mean excess returns of −1.9% per year and a four-factor alpha of −10.1%. Alphas increase monotonically across quintiles, with both the fourth and fifth equal-weighted quintiles earning statistically significant alphas. The annualized alpha for the equal-weighted highest jump probability quintile is 13.7%, leading to an alpha of 23.8% for the high-minus-low portfolio. Value-weighted portfolios exhibit a similar pattern. The alpha of the value-weighted long-short portfolio is 22.6%, about the same as that of the equal-weighted portfolio. The long-short portfolios marginally load positively on growth and negatively on momentum; however, the loadings are small, and excess returns are similar in magnitude to alphas. The panel also reports the average incidence of jumps across stocks in each portfolio on the day the portfolio is held. These realized jump probabilities show that our jump prediction model works well out of sample. Realized jump probabilities increase with increases in predicted jump probabilities: the high predicted jump probability portfolio has a 3.6% average probability of jumps, while the low portfolio has a 0.5% jump probability, creating a spread of 3.1% across portfolios.

The next panel examines weekly returns where portfolio formation skips a day after observing the variables

Table 7
Jump portfolio returns.
The table presents equal and value-weighted returns of portfolios formed from quintile sorts on out-of-sample predicted jump probabilities from the model in Table 6. We estimate model parameters using an expanding monthly window that uses data up to the end of the prior month. The model parameters are then applied to current, known stock characteristics to obtain predicted jump probabilities. For the daily frequency (Panel A), characteristics at day $t-1$ are used to calculate jump probabilities, and the portfolios are rebalanced daily. For the weekly frequency (Panel B), the portfolios are formed every Thursday using the variables known as of the end of the prior Tuesday, and the portfolio is held for an entire week. For the monthly frequency (Panel C), the variables are calculated at the last trading day of month $m-1$ and are used to form portfolios held for month m. *Excess return* is the average return for the portfolio in excess of the risk-free rate. The table reports coefficient estimates from time-series regressions of portfolio returns on Fama-French-Carhart factors. The last column of each panel reports the percentage of stocks in each portfolio that experience a jump during the period for which the portfolio is held. The portfolio construction sample period is January 1997 through April 2016.

Panel A. Daily portfolios

	Equal-weighted returns						Value-weighted returns						
	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Jump incidence
Low	−0.01%	−0.04%	1.04	0.55	0.08	−0.08	−0.02%	−0.05%	0.87	−0.01	0.02	0.04	0.53%
	(−0.37)	(−5.90)	(182.87)	(50.73)	(6.84)	(−10.40)	(−1.11)	(−5.26)	(120.15)	(−0.87)	(1.73)	(3.64)	(39.96)
2	0.02%	−0.01%	1.11	0.55	0.08	−0.06	0.01%	−0.02%	0.95	−0.06	0.04	0.06	1.04%
	(1.13)	(−1.61)	(210.44)	(54.56)	(7.77)	(−9.01)	(0.54)	(−2.42)	(150.42)	(−5.02)	(3.02)	(6.49)	(54.35)
3	0.04%	0.01%	1.17	0.56	0.00	−0.09	0.03%	0.00%	1.04	−0.05	−0.07	0.04	1.48%
	(1.92)	(1.44)	(226.17)	(57.00)	(0.38)	(−13.34)	(1.48)	(−0.02)	(172.65)	(−4.36)	(−5.69)	(5.51)	(59.32)
4	0.07%	0.03%	1.21	0.59	−0.04	−0.15	0.06%	0.03%	1.15	−0.04	−0.15	0.01	2.11%
	(2.70)	(4.56)	(216.78)	(54.79)	(−3.74)	(−20.46)	(2.81)	(3.87)	(170.88)	(−3.25)	(−11.54)	(1.08)	(66.04)
High	0.09%	0.05%	1.26	0.64	−0.07	−0.24	0.08%	0.04%	1.28	−0.04	−0.20	−0.07	3.60%
	(3.43)	(7.03)	(195.40)	(51.74)	(−5.76)	(−27.77)	(3.01)	(4.38)	(152.49)	(−2.32)	(−12.03)	(−6.31)	(78.28)
Hi −- Lo	0.10%	0.09%	0.23	0.09	−0.15	−0.16	0.10%	0.09%	0.41	−0.03	−0.22	−0.11	3.07%
	(8.57)	(9.52)	(27.59)	(5.73)	(−9.16)	(−14.57)	(5.64)	(5.95)	(32.52)	(−1.04)	(−9.02)	(−6.31)	(68.09)

Panel B. Weekly portfolios

	Equal-weighted returns						Value-weighted returns						
	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Jump incidence
Low	0.09%	−0.06%	1.08	0.54	0.14	−0.08	0.05%	−0.07%	0.88	−0.01	0.09	0.01	3.02%
	(0.97)	(−2.11)	(88.19)	(26.54)	(6.76)	(−5.90)	(0.69)	(−1.87)	(58.00)	(−0.30)	(3.68)	(0.78)	(38.72)
2	0.17%	0.01%	1.13	0.49	0.12	−0.06	0.10%	−0.02%	0.93	−0.11	0.03	0.02	5.65%
	(1.76)	(0.55)	(98.04)	(25.05)	(6.52)	(−5.17)	(1.28)	(−0.67)	(73.21)	(−4.95)	(1.45)	(1.55)	(46.97)
3	0.17%	0.01%	1.18	0.51	0.10	−0.09	0.12%	−0.02%	1.05	−0.03	−0.01	0.06	7.48%
	(1.63)	(0.25)	(104.97)	(26.83)	(5.39)	(−7.54)	(1.41)	(−0.65)	(82.80)	(−1.61)	(−0.46)	(4.79)	(48.84)
4	0.24%	0.08%	1.19	0.51	0.05	−0.14	0.19%	0.06%	1.08	−0.10	−0.13	−0.01	9.81%
	(2.26)	(3.34)	(110.94)	(28.23)	(2.55)	(−12.12)	(2.09)	(1.91)	(76.45)	(−4.07)	(−5.45)	(−0.67)	(52.36)
High	0.26%	0.12%	1.21	0.60	−0.01	−0.22	0.23%	0.09%	1.23	−0.08	−0.15	−0.01	13.80%
	(2.35)	(3.76)	(90.91)	(26.62)	(−0.62)	(−15.80)	(2.28)	(2.44)	(76.34)	(−3.02)	(−5.72)	(−0.58)	(60.38)
Hi − Lo	0.17%	0.17%	0.13	0.05	−0.15	−0.15	0.18%	0.16%	0.34	−0.07	−0.24	−0.02	10.78%
	(3.92)	(4.47)	(7.91)	(1.81)	(−5.35)	(−8.15)	(2.78)	(2.66)	(13.54)	(−1.73)	(−5.81)	(−0.83)	(51.92)

Panel C. Monthly portfolios

	Equal−weighted returns						Value-weighted returns						
	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Excess return	Intercept	Market-Rf	SMB	HML	UMD	Jump incidence
Low	0.52%	−0.20%	1.09	0.47	0.28	−0.10	0.29%	−0.23%	0.91	−0.11	0.12	0.01	16.62%
	(1.37)	(−1.64)	(37.93)	(12.59)	(6.78)	(−4.12)	(1.02)	(−1.77)	(29.39)	(−2.85)	(2.78)	(0.38)	(32.71)
2	0.70%	−0.03%	1.09	0.45	0.25	−0.06	0.53%	0.02%	0.88	−0.08	0.12	0.00	25.49%
	(1.89)	(−0.28)	(43.64)	(14.16)	(7.20)	(−2.97)	(1.96)	(0.18)	(38.62)	(−2.70)	(3.62)	(−0.03)	(40.31)
3	0.93%	0.19%	1.11	0.48	0.21	−0.07	0.48%	−0.12%	1.02	−0.07	0.07	0.04	31.35%
	(2.46)	(1.98)	(48.17)	(16.23)	(6.40)	(−3.37)	(1.55)	(−1.18)	(42.22)	(−2.18)	(1.89)	(1.76)	(44.79)
4	0.99%	0.25%	1.17	0.49	0.14	−0.09	0.94%	0.37%	1.09	−0.15	−0.10	0.00	37.50%
	(2.49)	(2.43)	(49.33)	(16.06)	(4.13)	(−4.39)	(2.79)	(3.04)	(38.13)	(−4.08)	(−2.52)	(0.04)	(50.25)
High	1.03%	0.34%	1.17	0.53	0.07	−0.20	0.81%	0.18%	1.19	−0.06	−0.22	0.03	44.64%
	(2.42)	(2.63)	(39.05)	(13.60)	(1.66)	(−7.96)	(2.12)	(1.19)	(34.00)	(−1.42)	(−4.40)	(0.99)	(56.67)
Hi −- Lo	0.51%	0.54%	0.08	0.06	−0.21	−0.10	0.51%	0.41%	0.28	0.05	−0.34	0.02	28.02%
	(2.97)	(3.30)	(2.19)	(1.22)	(−3.79)	(−3.16)	(2.01)	(1.76)	(5.01)	(0.71)	(−4.37)	(0.42)	(43.59)

used to construct jump probability, following Xing et al. (2010). We use values for tail probabilities along with implied and realized volatility as of the end of Tuesday to form portfolios that are held from Thursday to Wednesday. We skip a day to mitigate any biases that might arise from nonsynchronous trading between option and stock markets. Annualized mean excess returns for the equal-weighted long-short jump-risk portfolio are 8.7%, while four-factor alphas are 9.1%. Value-weighted excess returns and four-factor alphas are similar at 9.4% and 8.1%. The panel also presents average realized jump probabilities over the holding period for each portfolio. We count a week as a jump week for a given stock if there is at least one day that is a jump day in that week. Again, the model succeeds in predicting jumps out of sample at the weekly frequency. The spread in realized jump probability over the next week is 10.8% or 2.2% per day, which is a little smaller than the spread of 3.1% over the next day in Panel A. Not surprisingly, the predictive ability of our model for both returns and jumps diminishes somewhat over the next week, relative to over the next day.

Panel C shows monthly returns. We use estimates of jump probability from the end of the prior month and hold stocks for a month. Annualized alphas and excess returns for both equal and value-weighted versions of the long-short portfolio are now 5%–6%. The spread in jump probabilities also diminishes relative to the daily and weekly cases; it is now 28% per month or 1.3% per day. Overall, these results show a common pattern. The ability to predict jumps, as well as the alphas of the long-short portfolio, appear to diminish over time. Yet, alphas are a healthy 5%per year even for value-weighted returns in a sample of relatively large stocks that have traded options.

These results are consistent with the conclusions in Bali and Hovakimian (2009), who also find that jump risk carries a premium. However, they use the difference between call and put implied volatilities at moneyness of 1.1 and 0.9 as a measure of jump risk. The tail measure that we use is related to the average of, rather than the difference between, call and put implied volatilities. Hence, it is more robust to any information flow from option markets to stock markets on the direction of future stock returns, as shown in Xing, Zhang and Zhao (2010) for example.

How long do the alphas last? Fig. 3 examines this question by plotting weekly alphas and *t*-statistics for jump-probability long-short portfolios, as well as differences in realized jump probabilities for these portfolios, over the next 10 weeks. In particular, we estimate jump probabilities and form corresponding portfolios at the end of week w; then, we observe their returns for weeks $w+1$, $w+2$, $\ldots$, and $w+10$. The figure shows that equal-weighted alphas are significant for seven weeks; they diminish in economic and statistical significance thereafter. The ability of the model to predict jumps is also significant for seven weeks. The figure also plots alphas for value-weighted portfolios. The alphas for these portfolios display a similar pattern; however, their statistical significance diminishes quicker, and alphas are not statistically different from zero after two weeks. In Section 7 we show that value-weighted portfolios are more volatile than equal-weighted ones due to the influence of very large stocks and hence present a challenge for statistical inference. Fig. 3 also presents alphas for a version of the value-weighted portfolios in which we winsorize market capitalization at the 95% level to reduce the influence of the largest stocks. For all portfolio specifications, the alphas decline as the model's ability to predict jumps diminishes.

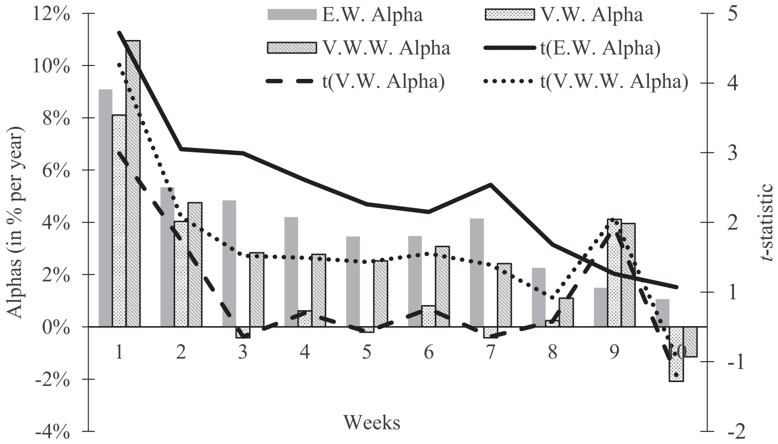
5.4. Idiosyncratic volatility and idiosyncratic jump probability

Ang et al. (2006) find that stocks with high realized idiosyncratic volatility over the past month have low average returns. In this section, we investigate the relation between idiosyncratic jump probability and idiosyncratic volatility sorted portfolios for two reasons. First, given the intuitive similarity between the two variables, it is surprising that one is negatively and the other is positively associated with returns. Second, a return observation is less likely to be classified as a jump for a stock with high idiosyncratic volatility relative to one with low idiosyncratic volatility. Hence, we expect (and confirm in unreported tests) that the idiosyncratic volatility of the lowest jump probability quintile is larger than that of the highest jump probability quintile. It is therefore possible that some of the negative alpha for the low jump probability portfolio may be related to the idiosyncratic volatility anomaly.

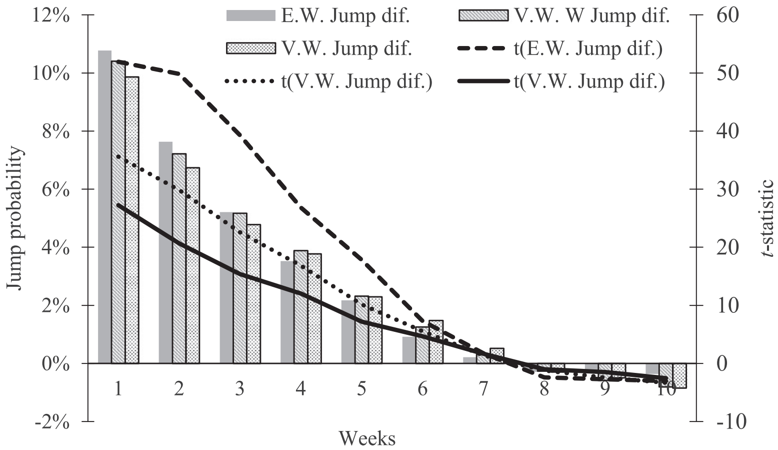
To investigate the relation between these two patterns, we perform sequential sorts into terciles, first on idiosyncratic volatility and then on predicted jump probability. Henceforth, we focus on weekly returns because they are a reasonable compromise between the potential for stale information in monthly returns and the frequent rebalancing of daily returns. As above, weekly portfolios are constructed using information known as of the end of Tuesday of each week and include returns from Thursday to the next Wednesday. Panel A of Table 8 presents equally weighted weekly alphas for these portfolios. We find that both patterns coexist. Stock returns increase monotonically within each idiosyncratic volatility tercile as jump probabilities increase. Stock returns also decrease monotonically within a given jump probability tercile as realized idiosyncratic volatilities increase. Thus, stocks with high jump probability earn high returns even after controlling for idiosyncratic volatility.

It is interesting to note that the average alpha across the three long-short jump probability portfolios after controlling for idiosyncratic volatility is 5% per year, which is smaller than the alpha differential between the univariate jump probability sorted quintile portfolios in Table 7 of 0.18% per week or 9.1% per year. Part of this difference may be because the quintile sorts in Table 7 result in a greater spread in realized jump probabilities (10.8%) than the tercile sorts in Table 8 (7.4%). A rough approximation suggests that we would expect a spread in returns of 6.2% ($9.1\% \times 7.4/10.8$). This suggests that controlling for idiosyncratic volatility reduces the alpha of the jump probability sorted portfolios by 1.2%.

Why is idiosyncratic jump risk priced differently than idiosyncratic volatility? Panel B of Table 8 provides a possible explanation. The panel presents the realized idiosyncratic volatility and realized jump incidences prior and subsequent to portfolio formation. Within a given idiosyncratic volatility tercile, as predicted jump probability increases, realized idiosyncratic volatility over the past 22 trading days generally goes down. However, realized volatility over the next 22 days goes up. Similarly, a dummy variable that is one if a stock experiences at least one jump in the prior week decreases as predicted jump probability increases in the two highest idiosyncratic volatility terciles (patterns are mixed in the lowest tercile). However, the incidence of jumps in the week after portfolio formation increases dramatically within each idiosyncratic volatility tercile as predicted jump probability increases. Thus, our predicted jump probability measure appears to capture the risk of jumps in the future,



(a) Panel A



(b) Panel B

Fig. 3. Performance persistence. We form portfolios based on quintile sorts on out-of-sample predicted jump probabilities known as of Tuesday of week w and hold them for a week starting Thursday of week $w+i$, where i ranges from zero to nine. Panel A reports Fama-French-Carhart alphas and t-statistics for equal-weighted, value-weighted, and winsorized value-weighted portfolios that are long the highest quintile of jump probability and short the lowest quintile. Panel B reports the difference in the average realized jump incidences between the stocks in the long and the short portfolios every week. The portfolio formation period is January 1997 to April 2016.

whereas the realized idiosyncratic volatility measure captures the realization of jumps or high idiosyncratic volatility in the past. This interpretation suggests that predicted jump probabilities measure a true future risk, which investors are averse to, while realized idiosyncratic volatility is related to a realization of uncertainty in the past, which is a worse predictor of future risk than predicted jump probability.

5.5. A decomposition of portfolio returns

Although the jump-risk prediction model succeeds in predicting both jumps and mean returns out of sample, it is not clear that the positive mean returns are due to stocks that jump. To examine this question, Table 9 presents a decomposition of weekly returns of each ex ante jump probability-sorted portfolio. As before, we identify a week as a jump week if the stock experiences a jump on any day that week. Also, rather than only considering probabilities of stock returns to exceed the admittedly ad hoc 3σ threshold we use to classify jumps, we also consider small jumps that are in the 2σ to 3σ band. Thus, each stock week is placed into one of three bands on the basis of the most extreme daily $z = |r^{idio}|/\sigma$. The bands are $z<2$, $2 \le z < 3$, and $z \ge 3$. For any week t and ex ante jump-probability quintile, the average excess return for band j is $\frac{1}{N_t}\sum 1_{i,j}(r_{i,t}-r_{f,t})$, where $1_{i,j}$=1 if z_i is in band $j \in \{1, 2, 3\}$; N_t is the number of stocks in the quintile portfolio at time t; and $r_{i,t}-r_{f,t}$ is the stock's excess return over the risk-free rate. We then present the fraction of stock days, mean returns, and FFC four-factor alphas for each of these bands in Panel A of Table 9. Note that as before, the decomposition takes into account the relative infrequency of extreme returns so that the sum of average returns across bands for a given jump probability portfolio equals the average returns for that portfolio.

First, the table shows that the realized fraction of return days with extreme returns increases as ex ante jump probability increases. For example, for the lowest jump

Table 8
Idiosyncratic volatility and jump probabilities.

The table summarizes characteristics of equal-weighted portfolios formed from sequential sorts on idiosyncratic volatility and jump probability. For each stock, idiosyncratic volatility is estimated as the standard deviation of the residuals from a daily FFC-factor model over the prior 22 trading days. Jump probabilities are obtained by applying logistic model parameters (estimated all observations up to the end of the prior month) to stock characteristics each Tuesday. The logistic model uses the average of the left-tail and right-tail measures as well as the log ratio of implied to realized volatility. Portfolios are formed each Thursday and held for one week. Panel A reports each portfolio's FFC alpha. Panel B reports the average idiosyncratic volatility of the constituents of each portfolio during the 22 days before and the 22 days after portfolio formation. The second set of results reports the incidence of jumps within the constituents of the portfolio in the week before portfolio formation and the week the portfolio is held. Panel C reports each portfolio's postformation idiosyncratic volatility with respect to the FFC factors.

	Jump probability							
iVol	Low	2	High	Hi-Lo	Low	2	High	Hi-Lo
Panel A. Portfolio alphas								
	Annualized alpha				*t*-stat			
Low	0.02%	0.08%	0.12%	0.09%	0.62	2.50	3.65	3.20
Medium	−0.02%	0.02%	0.08%	0.11%	−0.63	0.69	1.97	2.16
High	−0.07%	0.00%	0.05%	0.12%	−1.89	0.11	0.88	1.97
Hi −− Lo	−0.09%	−0.07%	−0.06%		−2.01	−1.31	−0.85	
Panel B. Portfolio characteristics before and after formation								
	Preformation (past)				Postformation (future)			
Annualized idiosyncratic volatility								
Low	1.33%	1.25%	1.15%	−0.18%	1.46%	1.57%	1.68%	0.22%
Medium	2.06%	2.01%	1.99%	−0.07%	1.91%	2.18%	2.54%	0.63%
High	4.21%	3.43%	3.20%	−1.01%	2.72%	3.02%	3.43%	0.71%
Realized jump probability								
Low	6.6%	6.2%	8.3%	1.7%	6.2%	9.8%	14.0%	7.8%
Medium	8.6%	6.3%	7.7%	−1.0%	4.5%	7.5%	12.1%	7.6%
High	13.0%	7.4%	7.3%	−5.7%	2.6%	5.4%	9.5%	6.9%
Panel C. Portfolio idiosyncratic volatility								
					Postformation (future)			
Low					0.91%	0.89%	0.90%	0.89%
Medium					0.97%	0.99%	1.20%	1.47%
High					1.11%	1.36%	1.85%	1.86%

probability portfolio, 89% of the constituent stocks have absolute idiosyncratic returns below two standard deviations, as opposed to 65% for the high jump probability portfolio. For all five portfolios, diffusive returns are small (between –0.36% and 1.94% per year) and are statistically indistinguishable from zero. These low diffusive returns are accompanied by exposure to the market factor (as in Table 7), resulting in negative alphas for each portfolio of around –5% per year. For the highest jump probability portfolio, absolute returns greater than 3σ are responsible for an annualized alpha of 6%, which is nearly the alpha of the high jump probability portfolio. For the high-minus-low portfolio, the diffusive band contributes an insignificant alpha of 0.8% per year, the 2–3σ jump band contributes 1.3%, and the 3σ and above band contributes almost 7%. These decompositions show that the jump probability portfolio returns are indeed driven primarily by jumps.

Panel A also shows that the jump-day premium does not exist if the jump is a surprise. An approximation of mean excess returns on jump days can be inferred from the ratio of mean excess returns to jump incidences in Panel A. Mean excess returns on 3σ jump days are negative and insignificant (–0.36% = −0.01%/3.02%) for the bottom jump probability quintile and increase to 1.04% for the top quintile.[11] This pattern is consistent with the jump-risk aversion hypotheses: investors only demand a premium if they realize that a jump is possible. When the jump is a surprise, there is no premium.

Panel B of Table 9 presents a similar decomposition of the returns of portfolios formed from sequential sorts on idiosyncratic volatility and jump probability. This panel highlights another difference between idiosyncratic volatility and idiosyncratic jump probability sorted portfolios. The negative alphas to high idiosyncratic volatility stocks accrue almost entirely from the diffusive component of returns, while the positive alphas to jump probability accrue from the jump component.[12] Understanding the

[11] This approximation is not exact because it assumes a constant mean jump incidence. In unreported results, we find the mean pooled jump-week returns exhibit the same pattern.

[12] The online Internet Appendix reports results using daily (instead of weekly) returns with qualitatively similar results. In particular, the univariate predicted jump portfolio returns are primarily driven by jumps, with more than two-thirds of the high-minus-low alpha due to extreme returns. The daily double sorts also attribute the negative alpha of idiosyncratic volatility portfolios to diffusive returns and the positive alpha of jump probability portfolios to jump returns.

Table 9
Portfolio return decomposition.
The table provides a decomposition of the idiosyncratic volatility and jump probability-sorted portfolio weekly returns into bands based on the ratio of component stock idiosyncratic return to idiosyncratic standard deviation. Each portfolio is formed from weekly sorts on ex ante jump probability (Panel A) and sequential double sorts on idiosyncratic volatility and ex ante jump probability (Panel B), as in Tables 7 and 8. Each portfolio's returns are decomposed into mutually exclusive and exhaustive bands based on $z_{i,t} = |r^{idio}_{i,t}|/\sigma_{i,t}$, where r^{idio} is stock i's daily idiosyncratic return relative to the Fama-French-Carhart model, and σ is its conditional idiosyncratic volatility. The bands, denoted by $j \in \{1, 2, 3\}$, are : $z_{i,\,t} < 2$; $2 \le z_{i,\,t} < 3$; and $3 \le z_{i,\,t}$. For a given week, a stock is assigned to one of the bands based on its most extreme daily return. For any week and portfolio, the excess return for band j is $\frac{1}{N}\sum 1_{i,j}(r_i - r_f)$, where $1_{i,\,j}$=1 if z_i is in band j, and zero otherwise, and N is the number of stocks in the portfolio; $r_i - r_f$ is the stock's excess return over the risk-free rate. Panel A reports excess returns, FFC alphas, and proportions of jump incidence for each jump probability-sorted portfolio. Panel B reports FFC alphas for the idiosyncratic volatility and jump probability-sorted portfolios. The portfolio construction sample period is January 1997 through April 2016.

Panel A. Jump probability-sorted portfolios

	$\lvert r^{idio}\rvert < 2\times\sigma$			$2\times\sigma \le \lvert r^{idio}\rvert < 3\times\sigma$			$\lvert r^{idio}\rvert \ge 3\times\sigma$		
	Ex. ret	Alpha	Incidence	Ex. ret	Alpha	Incidence	Ex. ret	Alpha	Incidence
Low	0.02%	−0.11%	88.53%	0.08%	0.06%	8.44%	−0.01%	−0.02%	3.02%
	(0.29)	(−3.80)		(4.81)	(4.66)		(−0.93)	(−1.56)	
2	0.04%	−0.08%	80.93%	0.09%	0.06%	13.43%	0.05%	0.03%	5.65%
	(0.53)	(−3.00)		(4.36)	(4.56)		(2.84)	(2.05)	
3	0.03%	−0.08%	76.43%	0.11%	0.08%	16.09%	0.03%	0.01%	7.48%
	(0.39)	(−3.28)		(4.44)	(5.11)		(1.67)	(0.73)	
4	0.03%	−0.07%	71.81%	0.11%	0.08%	18.38%	0.09%	0.08%	9.81%
	(0.45)	(−2.85)		(4.33)	(5.22)		(4.47)	(4.36)	
High	−0.01%	−0.09%	65.41%	0.12%	0.09%	20.79%	0.14%	0.12%	13.80%
	(−0.10)	(−3.33)		(4.05)	(5.79)		(4.97)	(4.99)	
Hi –- Lo	−0.03%	0.02%	−23.12%	0.04%	0.03%	12.35%	0.16%	0.13%	10.78%
	(−0.90)	(0.53)		(1.92)	(1.63)		(6.21)	(5.99)	

Panel B. Idiosyncratic volatility and jump probability double-sorted portfolios

	Jump probability											
	Low	Med.	High	Hi-Lo	Low	Med.	High	Hi-Lo	Low	Med.	High	Hi-Lo
iVol	$\lvert r^{idio}\rvert < 2\times\sigma$				$2\times\sigma \le \lvert r^{idio}\rvert < 3\times\sigma$				$\lvert r^{idio}\rvert \ge 3\times\sigma$			
Low	0.01%	0.02%	0.02%	0.01%	0.02%	0.03%	0.02%	0.00%	−0.01%	0.02%	0.07%	0.08%
	(0.25)	(0.92)	(0.77)	(0.55)	(1.65)	(2.33)	(1.84)	(0.36)	(−0.44)	(1.51)	(3.69)	(4.35)
Medium	−0.04%	−0.06%	−0.10%	−0.07%	0.03%	0.07%	0.10%	0.06%	−0.02%	0.02%	0.09%	0.11%
	(−1.44)	(−2.08)	(−3.29)	(−2.02)	(2.13)	(3.86)	(4.52)	(3.02)	(−1.01)	(0.83)	(3.61)	(4.36)
High	−0.13%	−0.18%	−0.30%	−0.17%	0.08%	0.14%	0.18%	0.10%	−0.02%	0.05%	0.18%	0.20%
	(−3.89)	(−4.95)	(−6.66)	(−3.97)	(4.68)	(6.23)	(6.70)	(3.53)	(−1.51)	(2.41)	(5.66)	(6.37)
Hi –- Lo	−0.14%	−0.20%	−0.32%		0.06%	0.10%	0.15%		−0.02%	0.03%	0.10%	
	(−4.13)	(−5.63)	(−7.47)		(3.29)	(4.80)	(5.32)		(−0.96)	(1.20)	(3.30)	

realized idiosyncratic volatility-return relation further is beyond the scope of this paper. Other research suggests that it is related to mispricing (Stambaugh et al., 2015), liquidity biases (Han and Lesmond, 2011), or skewness (Bali et al., 2011).

6. Testing idiosyncratic and systematic risk-based explanations

In this section, we examine the idiosyncratic and systematic risk explanations for the stylized facts about returns around jump days. The next two sections test whether systematic risk-based explanations are consistent with the data.

6.1. Is idiosyncratic jump risk really idiosyncratic?

Although in our identification of idiosyncratic jumps we exercise care in removing the influences of the FFC factors from both returns and volatility, it is possible that the abnormal returns to high jump probability stocks are driven by systematic, and not idiosyncratic, jump risk. Such a case could arise if the factor model is not well specified and the identified idiosyncratic jumps are correlated with systematic jumps. Back (1991) shows that if a portfolio has systematic jump-risk exposure, in the sense that the portfolio's jumps coincide with jumps in the stochastic discount factor, it will earn a risk premium.

If jumps in the high jump probability portfolio are systematic, they will not be diversified out in large portfolios. That is, the returns of the high jump probability portfolio will have more jumps than those of the low jump probability portfolio. Moreover, these jumps will be more likely to coincide with jumps in the market or other large portfolios.

Panel A in Table 10 shows the number of jumps in the daily returns of equal- and value-weighted portfolios constructed based on jump probability sorts. These are jumps in total returns, identified as days when the portfolio's absolute return is greater than three conditional standard deviations. Although we know from Table 7 that these portfolios differ substantially in the realized probability of jumps among the individual stocks that constitute each portfolio, the jumps in the portfolios' returns are similar across portfolios. The number of portfolio jumps ranges from 28 to 35 for equal-weighted portfolios and from 40 to 53 for value-weighted portfolios, with no clear pattern across portfolios. As a benchmark, the market portfolio has

Table 10
Systematic risk in jump portfolios.
The table shows the incidence of jumps in returns of jump probability-sorted portfolios as well as the ability of these portfolios to predict earnings growth. Panel A displays the number of jumps in returns of equal- and value-weighted portfolios constructed from quintile sorts on out-of-sample predicted jump probabilities. We construct the six daily portfolios from Table 7 on an equal- and value-weighted basis. For each portfolio, we identify jumps as daily absolute portfolio returns that are greater than three times the portfolio's conditional realized volatility. Cojumps are days when both the portfolio and the market experience a jump in returns. As a comparison, the market portfolio experiences 40 jumps over the sample. Panel B shows the coefficient estimates of a regression of earnings growth on the lagged returns of the weekly high-minus-low jump probability portfolios of Table 7 (Jump ret.) and the weekly returns of earnings announcers minus nonannouncers (Ann.ret.). We construct the announcer portfolio and the earnings growth series using the procedure in Savor and Wilson (2016). We then compound the weekly returns of the jump and earnings portfolios each quarter. The standard errors used are Newey-West-adjusted with a one-quarter lag.

Panel A. Jumps in jump portfolios

	Value-weighted			Equal-weighted		
	# of Jumps	# of Obs.	Cojumps	# of Jumps	# of Obs.	Cojumps
Low	45	4865	23	35	4865	19
2	40	4865	25	27	4865	16
3	40	4865	22	29	4865	19
4	52	4865	27	34	4865	19
High	53	4865	26	28	4865	19
High – Low	76	4865	7	62	4865	3

Panel B. Earnings growth predictability

	(1)	(2)	(3)
Intercept	−0.01%	0.13%	0.02%
	(−0.18)	(1.81)	(0.34)
Ann. ret.	0.042		0.044
	(2.47)		(2.60)
Jump ret.		−0.010	−0.018
		(−0.51)	(−1.13)
Obs.	78	78	78
Adj. R^2	13.96%	−0.88%	14.37%

40 jumps over the same period. The number of cojumps with the market is about the same for the extreme equal- and value-weighted portfolios. Interestingly, the long-short portfolio hedges a large fraction of the cojumps, presumably because the systematic jumps cancel out over the long and short legs. For example, for the equal-weighted portfolios, both the long and short legs have 19 cojumps with the market, but the long-short portfolio has only 3. Thus, it seems unlikely that the high returns to the long-short portfolio are due to the risk of cojumps with the market.

In the online Internet Appendix we report the event time returns to jumps conditional on aggregate market conditions. Specifically, we calculate jump-day returns in different subsamples based on whether certain aggregate variables are high (above median) or low (below median). The positive jump-day returns are present under various market conditions, that is, conditioning on market volatility, number of jumps, and market returns. These results reinforce the notion that the pattern we observe is unlikely to be due to some unobserved risk factor.

6.2. Do jump-risk portfolios predict aggregate cash flows?

Another systematic risk hypothesis for positive jump premiums is the mechanism in Savor and Wilson (2016) and Patton and Verardo (2012). Both papers argue that earnings announcers have high exposures to aggregate cash flow news because investors learn about market-wide cash flows from firm announcements. Savor and Wilson (2016) find that returns to a portfolio of earnings announcers predict aggregate earnings growth even after controlling for market returns. This mechanism can be responsible for our results if jumps contain information about aggregate cash flows. Given that our sample contains a large fraction of jumps that are not on earnings announcement dates, it is unclear ex ante if investors can glean aggregate information from jumps.

To test whether jumps contain aggregate market information, Panel B in Table 10 examines whether the high-minus-low jump probability portfolio predicts aggregate earnings growth. We measure earnings growth by aggregating earnings from all firms in our sample. As in Savor and Wilson (2016), earnings growth is the growth over the same quarter of the previous year to adjust for seasonality, and only firms with earnings in both quarters are included in the aggregation calculation. We compound the difference between equal-weighted announcer and nonannouncer portfolio returns within a quarter to obtain quarterly returns. First, we show that the results in Savor and Wilson (2016), that returns to announcers minus nonannouncers predict aggregate earnings growth in the next quarter, are present over our shorter sample. The first specification shows that the quarterly returns of the announcers minus nonannouncers portfolio predict the next quarter's earnings growth. However, the returns of the high-minus-low predicted jump probability portfolio do not predict earnings growth. Hence, the mechanism in Savor and Wilson (2016) does not apply in our context.

Additionally, Patton and Verardo (2012) show that the intraday β of earnings announcers increases drastically on the announcement date. This pattern is consistent with the predicted jump portfolio results in Table 7. For our daily portfolios, the $Mkt - Rf$ factor coefficient is 0.23 and 0.41 for equal- and value-weighted high-minus-low portfolios, respectively. However, this increase in systematic risk exposure is too small to explain the large returns to the strategy. The strategy's alpha of 9 bps is more than three times larger than the average market risk premium over our sample. The increase in β needs to be larger than three to justify the expected jump returns.

7. Limits to arbitrage

Why do the returns to the jump probability trading strategy persist? We examine two limits to arbitrage: exposure to idiosyncratic risk and transactions costs.

7.1. Idiosyncratic risk

A common assumption is that idiosyncratic risk diversifies out in portfolios with a relatively large number of stocks. If this is the case, the high jump probability trading strategy is akin to a "free lunch," with large returns and little risk. However, idiosyncratic risk vanishes only in the limit. In practice, institutions hold portfolios that contain a much smaller number of stocks than the market, presumably due to the transactions costs of trading and researching a large number of stocks. For example, Alti et al. (2012) report that the median mutual fund portfolio consists of less than 70 stocks. Pontiff (2006) argues that idiosyncratic risk is an important limit to arbitrage and that arbitrageurs will reduce their position in any opportunity with greater idiosyncratic volatility, all else equal. He also shows that there is no diversification benefit across opportunities: more available idiosyncratic opportunities do not mean more capital allocated per opportunity.

Panel A of Table 11 shows the idiosyncratic volatility of returns to the weekly long-short jump-risk trading strategy defined in Table 7, implemented using different numbers of stocks. We start with portfolios containing the top 35 and bottom 35 stocks in terms of predicted jump probability, leading to a long-short portfolio with positions in 70 stocks. The table reports the standard deviations of residuals of regressions of the lowest, highest, and high-minus-low portfolio returns on the FFC four factors. For portfolios with 35 stocks, the equal-weighted high jump probability portfolio has an annualized idiosyncratic standard deviation of 11.9%, and the long-short portfolio has an idiosyncratic standard deviation of 14.7% per year. As a comparison, the standard deviation of market returns is 15.9% per year over the same sample period. Thus, this idiosyncratic jump-risk portfolio exposes potential arbitrageurs to idiosyncratic volatility that is almost as large as the total volatility of the market. Matters are worse for value-weighted portfolios. The idiosyncratic volatility of the value-weighted long-short portfolio is 22.0% per year. This high volatility may be due to large stock jumps, which have a large effect on the volatility of the value-weighted portfolio. To test if this is the case, we use market capitalization winsorized at the 95th percentile of market equity that week to obtain portfolio weights. This value-weighted winsorized (VWW) portfolio has a lower idiosyncratic volatility than the value-weighted one at 19.4%.

Increasing the number of stocks to 70 for each side reduces the idiosyncratic standard deviation of the equal-weighted long-short portfolio to 11.7% per year. The idiosyncratic standard deviation of the value-weighted portfolio is still larger than the market's total standard deviation at 17.6% per year. We also analyze quintile-sorted portfolios and median-sorted portfolios. For the quintile-sorted portfolios, value-weighted idiosyncratic volatility is 13.4%. The alpha of the long-short quintile portfolio is nearly 6% per year, about the same as the market risk premium over the sample. The annualized information ratio of this strategy is 45%, which is comparable to the market's Sharpe ratio of 40% over the same period. Thus, this strategy has a similar risk-return trade-off as investing in the market.

Even for portfolios sorted into halves, with an average of 333 stocks in each half, the long-short portfolio has substantial idiosyncratic volatility. Thus, arbitrageurs that wish to execute the idiosyncratic jump-risk trading strategy will face substantial idiosyncratic risk. In fact, the quintile-sorted portfolio looks as good an investment, from a risk to return perspective, as the market. Investing in stocks with high jump probability is, by no means, a free lunch.

7.2. Transactions costs

The next limit to arbitrage we consider is transactions costs. As we have seen from Fig. 3, jumps appear to be relatively short-lived phenomena. The ability of our model to predict jumps dies out in seven weeks, as do the alphas. Thus, for arbitrageurs to buy high jump probability and sell low jump probability stocks, they need to rebalance their portfolios frequently. Transactions costs associated with rebalancing can diminish the profits of the jump-risk trading strategy, making it uneconomical for arbitrageurs. If the jump-risk premium is due to mispricing that is not fully arbitraged away due to transactions costs, returns to the strategy should be higher in stocks with higher transactions costs. Panel B of Table 11 analyzes whether alphas for the jump-risk premium trading strategy are related to transactions costs. Our measure of transactions costs is the Gibbs estimate of the Roll transaction cost measure from Hasbrouck (2009). This measure is based on the Roll (1984) model in which the observed price (p_t) reflects the efficient price (m_t) plus a cost that depends on trade direction ($q_t \in \{-1, +1\}$) and the trading cost (c):

$$m_t = m_{t-1} + u_t,$$
$$p_t = m_t + cq_t,$$

where u_t is a zero-mean noise term. Hasbrouck (2009) estimates transactions costs using a Bayesian sampling estimator in a variant of this model that also includes an adjustment for market returns.[13] Novy-Marx and Velikov (2016) also use this measure to estimate the trading costs of anomalies. Every week, we first sort stocks into terciles

[13] We thank Joel Hasbrouck for providing code to estimate the transaction costs based on this model.

Table 11
Limits to arbitrage.
The table presents the idiosyncratic volatility of returns of jump probability portfolios as well as alphas for portfolios formed from sorts on jump probability and transaction costs. For Panel A, we form portfolios based on sorts on out-of-sample predicted jump probabilities every Tuesday and hold them for a week from Thursday to the next Wednesday. The high (low) portfolios consist of the 35 stocks, 70 stocks, fifth, and half of the sample, respectively, with the highest (lowest) predicted jump probability. The portfolios are formed either with equal weights (EW), value weights (VW), or winsorized value weights (VWW), where market capitalization is winsorized at the 95% levels each week. In each specification, we report the annualized standard deviation of weekly return residuals from a regression of each portfolio's returns on the Fama-French-Carhart four factors. In Panel B, we sort all stocks based on the prior year's transaction costs into terciles. We then form portfolios based on tercile sorts on out-of-sample predicted jump probabilities within each cost tercile. We report Fama-French-Carhart alphas of the high-minus-low jump probability portfolios within each transaction cost tercile. Transaction cost estimates are obtained following the method of Hasbrouck (2010). The sample excludes stocks whose price 31 days before portfolio formation is below $5 and portfolio formation period is 1997–2016.

Panel A. Portfolio idiosyncratic volatility

		35 Stocks	70 Stocks	Quintile	Half
	EW	9.1%	7.7%	6.4%	5.3%
Low	VW	12.7%	10.3%	8.0%	5.1%
	VWW	11.7%	9.3%	7.3%	4.9%
	EW	12.0%	9.0%	7.0%	5.0%
High	VW	16.4%	11.9%	8.4%	5.0%
	VWW	14.2%	10.2%	7.5%	4.3%
	EW	14.5%	11.5%	8.9%	5.4%
HML	VW	21.6%	17.6%	13.4%	8.7%
	VWW	19.0%	15.4%	12.0%	7.4%

Panel B. Transactions costs

	Equal-weighted			Value-weighted winsorized			Value-weighted		
Cost	Alpha	t(Alpha)	Jump	Alpha	t(Alpha)	Jump	Alpha	t(Alpha)	Jump
Low	0.09%	2.61	8.05%	0.14%	2.89	7.5%	0.13%	2.18	7.1%
Med	0.13%	3.05	8.72%	0.17%	2.77	8.4%	0.15%	1.93	8.2%
High	0.18%	3.36	8.56%	0.27%	3.29	8.5%	0.22%	2.54	8.7%

based on transactions costs from a prior period (typically the last calendar year, but the time period could be shorter if a stock moves to a new exchange, as in Hasbrouck 2009). Within each cost tercile, we sort the stocks into terciles based on our predicted jump probabilities.

Panel B of Table 11 reports alphas for the portfolio that is long the top jump probability tercile and short the bottom tercile. As before, we form portfolios based on information as of Tuesday and hold them from Thursday to the next Wednesday. We report alphas from equal- as well as value-weighted portfolios. Additionally, we also form value-weighted winsorized portfolios by winsorizing market equity at the 95th percentile to obtain more precise estimates based on the evidence in the prior section that winsorizing market equity reduces the idiosyncratic volatility of the portfolio. For equal-weighted portfolios, the tercile with the lowest transaction costs yields the lowest strategy alpha at 0.1% per week or 4.5% per year, while the other two terciles have annualized alphas of 6.6% and 9.4%, respectively. Similarly, the alphas of the value-weighted winsorized jump strategy increase monotonically as transaction costs increase. As expected, value-weighted portfolios are noisier; however, the long-short jump probability strategy alpha is increasing in transaction costs.

The results of this analysis reveal that transactions costs can act as a limit to arbitrage in our setting. Despite the idiosyncratic nature of jump risk, forming portfolios to ensure that markets do not price such risk is costly.

8. Further tests and robustness

In this section, we examine whether the negative drift before jumps is consistent with the idiosyncratic jump-risk hypothesis and discuss the results of robustness tests.

8.1. Is the drift before jumps consistent with the idiosyncratic jump-risk hypothesis?

Our tests thus far have focused on the ex ante jump-risk premium. We have not considered the negative returns before jumps because these results require an ex post identification of jumps and hence can have many possible explanations. However, the prejump returns are a part of the pattern in returns around jumps and provide grounds for further tests of our hypotheses. We report results of such tests in this section, noting that these tests can only invalidate a hypothesis but by themselves are not sufficient to confirm any particular hypothesis. We specifically examine changes in jump portabilities before all jumps and jumps on earnings announcements days. We also examine reversals as a possible explanation for our results.

8.1.1. Changes in jump probabilities before jumps

According to the jump-risk hypotheses, the negative drift before jumps arises if jump probabilities increase on average over the 30-day period before realized jumps, and investors push prices down as jump probabilities increase.

The evidence in Fig. 2 suggests that left- and right-tail jump probabilities and implied volatilities do increase on average before realized jumps. In the online Internet Appendix, we show that the probability of jumps on day t is significantly correlated with the change in jump probabilities over $t-30$ to $t-1$. The realized likelihood of jumps more than doubles (2.44%) when jump probabilities increase relative to when they decrease (0.95%) over the prior 30 days. When we condition on a jump at time t, jump probabilities increase on average in the 30 days before the jump by 1%. We also show that the change in jump probabilities over the prejump period is inversely correlated with returns over the same period. Thus, the drift is consistent with the jump-risk hypotheses.

An important caveat to these results is that they are contemporaneous correlations and hence do not speak to causation. It is possible that changes in jump probabilities cause the negative drift, as the jump-risk hypotheses imply. It is also possible, however, that jumps are more likely following extremely negative returns. Thus, the results on the correlation between the drift and changes in jump probability are by no means conclusive evidence for the jump-risk hypotheses by themselves, because these results could have other explanations. However, when combined with the other results presented earlier (e.g., the ex ante jump-risk premium), they paint a consistent picture.

Section 3.4 shows that a negative drift also exists before jumps on earnings announcement dates. This result is inconsistent with the compensator hypothesis because this hypothesis requires the date of the jump to be stochastic. However, this result is consistent with the jump-risk hypotheses. In particular, although the date of a potential jump is known, the probability that it will indeed occur is not constant. As in the case of other realized jumps discussed above, to be consistent with the jump-risk hypotheses, jump probabilities should increase on average before jumps on earnings announcement days. We find that this is indeed the case. Jump probabilities before jumps on earnings dates increase by 1.2% on average. Also, we show in the online Internet Appendix that the absolute magnitude of the negative drift before earnings announcement jumps is proportional to the change in jump probability over the 30 days prior to the jump.

8.1.2. Can reversals explain the negative prejump returns?

Another possibility is that the negative prejump returns are a manifestation of short-term reversals that have been documented by prior research (Jegadeesh, 1990). We observe a reversal-like pattern with positive mean jumps following a negative mean drift. If extremely negative (positive) returns are followed by positive (negative) mean jumps, and jumps are more likely after negative returns as discussed above, then the mean jump-day return will be positive and the prejump returns will be negative.

There are two prominent explanations for reversals: bid-ask bounce (Kaul and Nimalendran, 1990) and overreaction (Subrahmanyam, 2005). We know from the results in Table 2 that the pattern in prejump and jump-day returns remains if we compute returns from midpoints of bid and ask quotes. Hence, bid-ask bounce-based reversal cannot account for the patterns we observe. In the online Internet Appendix, rather than conditioning on jumps and looking back in time to estimate the prejump drift, we condition on returns over a 30-day period (which are observable in real time) and report the incidence of jumps and jump-day returns over the next day. We find a negative correlation between returns and realized jump probability, consistent with the discussion above. However, we observe a similar fraction of positive to negative jumps following negative and positive extreme returns. Jump-day returns are positive on average following both positive and negative extreme returns, and reversals are observed in the diffusive component, not the jump component, of returns. Hence, the patterns in returns around jumps are not likely to be a manifestation of reversals.

8.2. Robustness to alternate specifications

We subject our key results to a battery of robustness tests. We summarize the results of these robustness tests below; detailed tables are in the online Internet Appendix. The positive mean return on jump days, negative returns before jumps, and the ex ante jump-risk premium at the daily, weekly, and monthly frequency remain if we use:

i. Different thresholds to identify jumps. Results remain significant if we use two or four conditional standard deviations as our threshold for identifying jumps.
ii. Idiosyncratic bipower variation, rather than standard deviations, as the denominator in the definition of jumps. This is the estimator proposed by Lee and Mykland (2008).
iii. Identifying jumps in weekly, rather than daily, returns. In particular, these results suggest that the strategic release of bad news by managers needs to occur at an even lower frequency than the weekly frequency to cause the mean positive jump-day returns.

Finally, in the online Internet Appendix we show that the positive average returns on idiosyncratic jump days are not driven by the positive average returns on macroeconomic announcement days documented by Savor and Wilson (2013). Both patterns coexist in the data.

9. Conclusion

We show that returns on jump days are large and economically meaningful. With 4.5 jumps a year, and average returns on jump days of 2.5%, jump days account for a large portion of the average returns of a typical stock. We also show that these jumps are often associated with important firm-specific news and that the high average jump-day returns are not due to any particular type of news.

We consider three explanations for the positive mean jump-day returns: a premium for idiosyncratic jump risk, a compensated jump process with a positive mean, and a compensation for systematic risk. To distinguish between the risk-based and the compensated jump process explanations, we test whether the jump-risk premium exists ex ante. In particular, we predict jumps out of sample using information in option prices and examine the returns of a trading strategy that buys (sells) stocks in the top (bottom) quintile of predicted jump probability. We find that this strategy earns significantly positive mean returns and four-factor alphas, providing evidence in favor of the risk-based explanations. Further, several tests do not support the systematic risk-based explanation. The returns of the high jump probability portfolio do not exhibit more jumps than those of the low jump probability portfolio, indicating that the jumps are indeed idiosyncratic. Also, the returns of the high-minus-low jump probability portfolio have low market exposure and do not predict aggregate cash flow growth, ruling out two possible systematic-risk channels.

Finally, we find that the returns to the high-minus-low jump probability portfolio are related to limits to arbitrage. Returns are higher in stocks with higher transactions costs, and the jump-risk trading strategy is exposed to substantial idiosyncratic risk. These results support the hypothesis that costly to arbitrage mispricing, rather than systematic risk, is responsible for the idiosyncratic jump-risk premium.

Appendix

In this section, we generalize the Merton (1976) model to allow for a richer class of jump processes without the memoryless property. Using this framework, we illustrate more formally the conditions under which the compensator for jumps can lead to the empirical regularities that we observe. Specifically, we model an individual stock by specifying the stochastic differential equation governing the log-price of the stock s_t:

$$ds_t = \mu_t dt + \sigma_t dB_t + Z_t dN_t, \tag{5}$$

where B_t is a standard Brownian motion, N_t is a counting process, and Z_t is a scalar random variable. We further assume that N_t is independent of the Brownian motion B_t, and the Z_t are serially independent and are independent of the counting process N_t and the Brownian motion B_t. We place no restrictions on the drift and diffusion processes μ_t and σ_t, except that they are independent of the counting process N_t and the jump magnitude Z_t. This assumption of independence is critical in our model, as it guarantees that the jump elements (N_t and Z_t) are indeed idiosyncratic. It is important to note that the standard assumptions about a probability space and filtration $\mathcal{F}_t$ apply.

The stochastic process described here can capture the empirical regularity that we observe of positive jump returns. The only condition is that jumps have a positive mean, i.e., $E[Z] > 0$. In order to investigate returns preceding jumps, we are interested in the returns over a prespecified interval τ:

$$s_t - s_{t-\tau} = \int_{t-\tau}^{t} \mu_u du + \sigma_u dB_u + Z_u dN_u.$$

To fix concepts, we define a general form of the counting process N_t using the arrival intensity λ_t:

$$\begin{cases} P(dN_t = 0) = (1 - \lambda_t)dt + o(dt) \\ P(dN_t = 1) = \lambda_t dt + o(dt) \\ P(dN_t \geq 2) = o(dt) \end{cases}, \tag{6}$$

where λ_t is a nonnegative stochastic process independent of the continuous part of the price dynamics and the jump size process Z_t. Given this independence, the last part of the integral above satisfies the following:

$$E\left[\int_{t-\tau}^{t} Z_u dN_u\right] = E[Z]E\left[\int_{t-\tau}^{t} \lambda_u du\right].$$

Theorem 1. If $E[Z_t] > 0$, then conditioning on a jump at $t + \epsilon$ reduces expected returns over $(t - \tau, t)$, if and only if it also reduces the jump intensity over $(t - \tau, t)$:

$$E[s_t - s_{t-\tau} | dN_{t+\epsilon} = 1] < E[s_t - s_{t-\tau}]$$
$$\iff E\left[\int_{t-\tau}^{t} \lambda_u du | dN_{t+\epsilon} = 1\right] < E\left[\int_{t-\tau}^{t} \lambda_u du\right].$$

Proof. The expected continuously compounded return:

$$E[s_t - s_{t-\tau}] = E\left[\int_{t-\tau}^{t} \mu_u du + \sigma_u dB_u + Z_u dN_u\right]$$
$$= E\left[\int_{t-\tau}^{t} \mu_u du\right] + E[Z]E\left[\int_{t-\tau}^{t} \lambda_u du\right],$$

Conditioning on a jump at time $t + \epsilon$ for some $\epsilon > 0$:

$$E[s_t - s_{t-\tau} | dN_{t+\epsilon} = 1]$$
$$= E\left[\int_{t-\tau}^{t} \mu_u du + \sigma_u dB_u + Z_u dN_u | dN_{t+\epsilon} = 1\right]$$
$$= E\left[\int_{t-\tau}^{t} \mu_u du\right] + E[Z]E\left[\int_{t-\tau}^{t^-} \lambda_u du | dN_{t+\epsilon} = 1\right],$$

where we used the independence of N_t from μ_t, σ_t, and B_t to obtain:

$$E\left[\int_{t-\tau}^{t} \mu_u du + \sigma_u dB_u | dN_{t+\epsilon} = 1\right]$$
$$= E\left[\int_{t-\tau}^{t} \mu_u du + \sigma_u dB_u\right].$$

From the two expressions above we can derive:

$$E[s_t - s_{t-\tau}] - E[s_t - s_{t-\tau} | dN_{t+\epsilon} = 1]$$
$$= E[Z]\left(E\left[\int_{t-\tau}^{t} \lambda_u du\right] - E\left[\int_{t-\tau}^{t} \lambda_u du | dN_{t+\epsilon} = 1\right]\right).$$

This term is positive iff $E[\int_{t-\tau}^{t} \lambda_u du] > E[\int_{t-\tau}^{t} \lambda_u du | dN_{t+\epsilon} = 1]$, which completes our proof. □

Note that this setup nests the traditional Poisson jump process, where $\lambda_t = \lambda, \forall t$. As discussed in the main text, such processes cannot explain the prejump drift because:

$$E\left[\int_{t-\tau}^{t} \lambda_u du\right] = E\left[\int_{t-\tau}^{t} \lambda_u du | dN_{t+\epsilon} = 1\right].$$

Conditioning on a jump at time $t + \epsilon$ does not alter the distribution of jumps in any interval before t (the memoryless property). As a result, the expected returns before a jump are not affected by conditioning on the occurrence of a jump at $t + \epsilon$. The same logic applies to doubly stochastic (or Cox) Poisson processes in which λ_t is stochastic but independent of the actual jumps.

The negative drift before jumps can be consistent with the model we present here if there is a negative serial correlation between jumps. More precisely, given a jump at $t + \epsilon$, if the jump intensity process λ_u is lower for $u \in [t - \tau, t]$ than its unconditional mean, then we will observe a

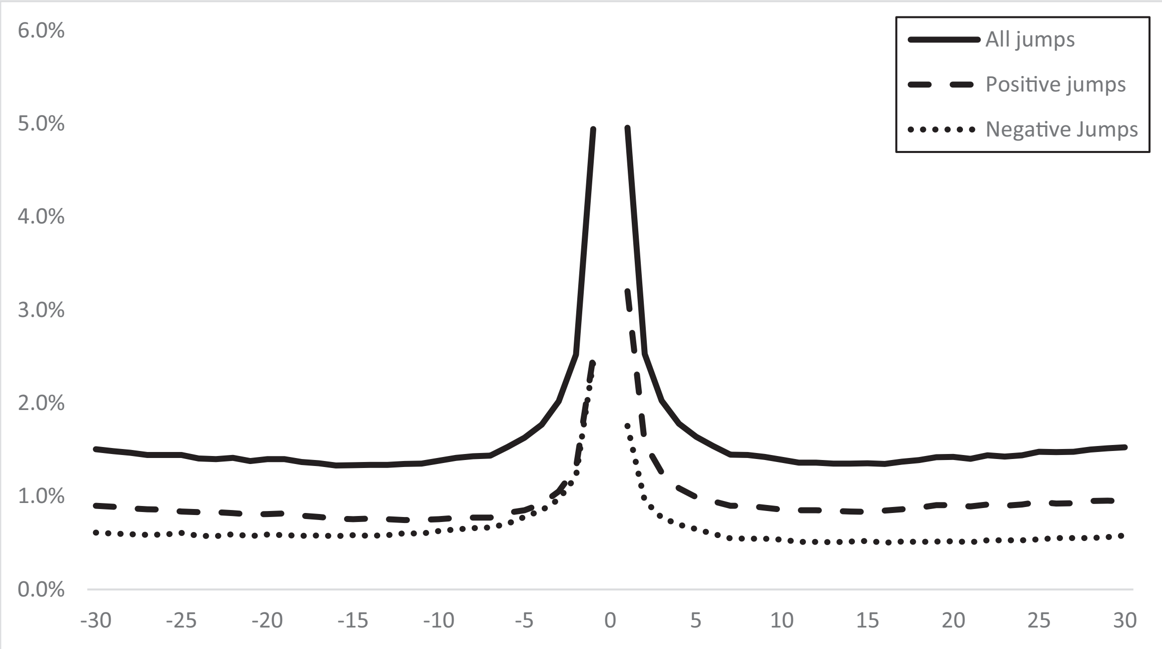


Fig. A1. Jump incidence. The figure represents the time series of the average jump incidence in event time. For each jump incident in our sample, we calculate the empirical incidence of positive and negative jumps in the 60-trading-day window surrounding the jump. A jump on date t is defined as an absolute daily idiosyncratic return in excess of three conditional standard deviations, where the return is idiosyncratic relative to the Fama-French-Carhart model, and the conditional standard deviation is based on an exponentially weighted moving average model. The solid line represents all jumps, and the dashed and dotted lines represent positive and negative jumps, respectively. The sample excludes stocks whose price is below $5 at $t-31$, and the sample period is 1926–2016.

negative drift. Such processes have not been studied extensively in the literature to the best of our knowledge. In fact, the literature finds evidence consistent with "self-exciting" jump processes, which have positive (and not negative) serial correlation in jump incidence (see, for example, Aït-Sahalia et al., 2015). Nevertheless, processes with negative correlation in jump incidence could arise if there is one piece of news that could cause a jump. The revelation of that news at some point in time t precludes jumps immediately before and after t. Although jump probabilities are high ex ante, we will not see any jumps until t ex post. This would give rise to a negative drift before t due to the compensator.

Fig. A1 presents preliminary evidence on the degree of serial dependence in idiosyncratic jumps in the data by presenting realized jump probabilities in the 60-day window around jumps. Note that the series of all jumps in the figure is symmetric across the periods before and after jumps by construction. Given that the figure is constructed in event time, two consecutive jumps appear both in the pre- and post-event parts of the graph. For example, if there is a jump on day t and one on day $t+5$, for the first event there is a jump in the post-event window on day $+5$, and for the second there is one in the pre-event window on day -5.

The figure shows evidence of self-exciting jumps in the 10 days around jumps. Realized jump probabilities are substantially higher in this period. However, jump probabilities decline in the period $(t-30,\ t-10)$. Overall, we observe slightly smaller jump intensities during the 30 trading-day prejump window of 1.6% a day compared with the unconditional mean of 1.8%. However, the magnitudes are too small to justify the drift that we observe. With an average jump size of 2.5%, the difference in jump intensity of 0.2% translates into an expected return differential of only 0.005% per day, or 0.16% over the 30-day prejump period. This is much smaller than the –1.9% drift we observe in that period. The magnitude of the drift that we observe can only be explained by the compensator if jumps do not occur at all in the prejump window, which is clearly inconsistent with the data.

Thus, two requirements of the compensator hypothesis explanation, uncertainty about the timing of the jump and negative serial correlation in jump incidence, are both inconsistent with the data.[14] Section 5 of the paper focuses on more direct tests of the compensator hypothesis using the ex ante jump-risk premium.

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[14] Section 3.4 shows that a negative drift exists before earnings announcements, whose dates are prescheduled.

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