The Information Content of The Implied Volatility Surface: Can Option Prices Predict Jumps?*

Abstract

We ask whether option prices contain information on the likelihood and direction of jumps in the underlying stock prices. Applying the partial least squares (PLS) approach to the entire surface of the implied volatilities, we show that option prices can successfully predict downward jumps in stock prices, but not upward jumps. The PLS estimated downward jump factor can predict stock returns with a spread of 1.53% per month between stocks predicted to have the lowest probability of downward jumps and stocks predicted to have the highest probability of downward jumps. Both put and call option prices, and options of both short and long maturity contribute to the predictability. Furthermore, the predictability of the downward jump is robust to many firm characteristics as well as options related variables. Consistent with the notion that informed investors trade in the options markets to profit from negative information in order to circumvent the short-sale constraint, we find that stronger predictability is associated with tighter short-sale constraint in the equity market, and in periods when the market has poor performance.

JEL Classification: G11, G14

Keywords: Options, Implied Volatility, Jumps, Machine Learning, PLS, Predictability

1 Introduction

Previous studies (e.g. Black, 1975; Easley, O'Hara, and Srinivas, 1998) suggest that some informed traders choose to trade options due to the embedded leverage and the absence of short-sale constraint in the options markets. Presumably, trading options is profitable only if the underlying stock price moves in the expected direction and the change in the stock price is large enough to cover the option premium and the transaction costs. As a result, traders with information about relatively large directional price movements of the underlying stocks, which we call "jumps" hereafter, have better incentives to trade options. In this paper, we ask whether such information may be reflected in option prices and how to efficiently extract that information. More specifically, we seek to answer the following two questions. First, do option prices contain differential information on the likelihood and direction of jumps in the underlying stock prices? Second, if such information can be identified, does it allow investors to form profitable trading strategies?

To efficiently extract information from the option prices, we employ the partial least squares (PLS) approach pioneered by Wold (1966, 1975) and extended by Kelly and Pruitt (2013, 2015). Black-Scholes option implied volatility (Black and Scholes, 1973; Merton, 1973) is often considered as a good proxy for the information contained in option prices in the literature. At each period, there are many relevant options which differ by the strike price or moneyness, and maturity. In addition, there are both call and put options of various moneyness and maturity. Previous literature to estimate jump risk and jump probability often takes the difference of the implied volatility (IV) between the put and call with somewhat arbitrary choice, for example using the shortest maturity at-the-money options. In this paper, instead of choosing options with arbitrary moneyness and maturities, and taking the difference between the put and call options, which may result in the loss of information, we use all available option IVs. In other words, we use the entire IV surface to extract the information about jumps in the underlying stock prices.

Similar to other machine learning tools, the PLS approach is effective at extracting common information (latent factor) from a large cross section of variables and substantially reducing the dimension of the problem. This is ideal for our setting because the entire IV surface contains a large number of IVs (260 IVs) for each period. A similar approach is the principal component analysis (PCA). However, the key difference lies in what information is extracted. PCA extracts the common variations based on the covariance structure of the variables, and therefore the information extracted may not be relevant for forecasting jumps.[1] On the other hand, by projecting to the observed jumps, the PLS approach extracts information that is most relevant to the prediction of jumps in stock returns. In addition, by projecting to the downward jumps and upward jumps separately, the PLS approach enables us to estimate separately the downward jump (latent) factor and the upward jump (latent) factor.

Empirically, we extract out-of-sample jump factors and test whether they are related to the realized jump probabilities and future returns. We define downward (upward) jumps as returns below (above) a certain threshold. For example, with a −15% threshold, stocks in top (bottom) deciles sorted by the downward jump factor has a downward jump probability of 17% (11%), with a spread of 6% that is statistically significant. Not surprisingly, the downward jump factor is negatively related to stock returns with the bottom and top deciles earn 1.39% and −0.14%, respectively. This leads to a long-short trading strategy with an average monthly return of 1.53%. The risk-adjusted alpha is 1.29%, which is highly significant. In contrast, the upward jump factor cannot significantly predict future returns. These results are consistent with the notion that informed traders would choose to trade on the option market to take advantage of the embedded leverage and to avoid the costly short selling of stocks.

We further explore the source of information along two dimensions. The first is whether

[1] Indeed, results not shown in the paper suggest that there is no out-of-sample predicability using the PCA approach.

call or put options are more informative than the other in predicting the downward jump probabilities and future returns. We find that the downward jump factor extracted from the call options alone fails to predict the downward jump probabilities and future returns, whereas the downward jump factor extracted from the put options alone still retains the significant predictive power. However, it is weaker than that of using both the call and put options. The second source of information we investigate is whether IVs with different time to maturity contain different information. One would, *a priori*, expect that only options with exactly one month to maturity should contain the most relevant information for the prediction of monthly jumps and returns, and that options with longer maturity may not provide additional information. While options with one month to maturity do contain information on the likelihood of downward jumps for the next month, more information or better information is contained in the options with longer maturities. This is likely due to the fact that all stock options examined in our sample are American options, which can be exercised prior to expiration, making these options relevant for one-month prediction.

Next, we show that the predictive power of the downward jump factor is robust to a host of control variables in the Fama-MacBeth regressions that include various firm characteristics such as book-to-market, change in 6-month momentum, earnings announcement return, one-month reversal, return volatilities, etc., as well as option-related variables that are shown to forecast future stock returns such as implied volatility slope/skewness, volatility spread, option to stock volume ratio, etc. It is especially of interest that our downward jump factor has information about future returns that is independent of the information contained in the previously identified IV related variables such as implied volatility skewness, volatility spread, etc.

We further explore the economic channel of the predictability of downward jump probabilities and future returns. Since informed traders use options to circumvent the short-sale constraint, we would expect stronger predictability with stocks subject to tighter short-sale constraint. We use three approaches to test this economic channel. First, we use the ratio of short interest over the total number of shares outstanding as a proxy of the short-sale constraint. We indeed observe stronger predictive power of the downward jump factor for stocks with tighter short-sale constraint in the Fama-MacBeth regressions. Second, following Berkman, Dimitrov, Jain, Koch, and Tice (2009), we use institutional holding to measure the tightness of short-sale constraint; firms with high institutional holding generally have less binding short-sale constraint. Similarly, we find stronger predictive power of the downward jump factor for stocks with tighter short-sale constraint. Finally, we exploit the Pilot Program of Regulation SHO as a quasi-experiment to examine the effect of loosening the short-sale constraint on the predictive power of our estimated jump factors. The regression results show that for the pilot stocks during the period when Regulation SHO is in effect, the predictive power of the downward jump factor is statistically weaker.

Finally, we test the robustness of our results along several dimensions. First, we divide the sample period into two subperiods via different criteria such as market return, volatility, sentiment, business cycle, etc. Second, we divide the sample of stocks into big, small, and microcap stocks. Third, we conduct sequential double sorts to control for the tightness of the short-sale constraint. Furthermore, we use idiosyncratic return jumps instead of return jumps to estimate the downward jump factor and examine its predictive power. Lastly, we investigate the predictive power over longer investment horizons. The results show that the predictive power of the downward jump factor is very robust, and is mainly driven by the idiosyncratic return jumps.

Our paper is related to the literature that estimates and forecasts jumps in stock prices. One strand of the literature models stock returns with jumps, which has a long history that goes back to Press (1967). Most studies use either stochastic volatility jump diffusion models or GARCH-jump models to model the return data-generating process. Examples are Andersen, Benzoni, and Lund (2002), Bates (2000), Chernov, Gallant, Ghysels, and Tauchen (2003), Eraker, Johannes, and Polson (2003), Maheu and McCurdy (2004), Maheu, McCurdy, and Zhao (2013), and Xiao and Zhou (2018) to name a few. Another strand of literature uses options to estimate and forecast jumps. For example, Pan (2002) examines the joint time series of the S&P 500 index and near-the-money short-dated option prices with an arbitrage-free model, capturing both stochastic volatility and jumps.

Our paper is more closely related to the literature that not only estimates or forecasts jumps or jump related quantities but also uses those jump related quantities to forecast future returns. For example, Yan (2011) argues that average jump size is related to expected returns and provides evidence that the slope of option implied volatility smile, which proxies for the jump size can predict future returns. Jiang and Yao (2013) identify jumps in daily returns and show that jumps can fully explain size and illiquidity effect and also account for the value premium. More recently, Kapadia and Zekhnini (2019) and Bégin, Dorion, and Gauthier (2019) present new evidence that jumps are related to stock returns cross-sectionally. Our paper differs from the literature in two important ways. First, we use the entire IV surface to construct the jump factor. Previous studies such as Xing, Zhang, and Zhao (2010) and Yan (2011) only use a few IVs and choose them in somewhat *ad hoc* ways. Second, we differentiate downward from upward jumps, whereas most previous studies do not make the distinction.[2] Since informed traders do not necessarily need to use options to take advantage of upward jumps, it allows us to present more convincing evidence of the predictability, separating the downward jumps from the upward ones.

On this note, our paper is also related to the literature that studies downside risk or tail risk. Several recent papers such as Bollerslev and Todorov (2011), Bali and Whitelaw (2014), Kelly and Jiang (2014), Van Oordt and Zhou (2016), and Chapman, Gallmeyer, and Martin (2018), propose various ways to capture the downside risk or tail risk and analyze its impact on individual stock returns or the market aggregate returns. Our downward jump factor can also be used to measure the downside risk.

The rest of the paper is organized as follows. Section 2 describes the rationale and procedure of extracting the jump factors from options prices using the PLS approach. Sec-

[2]Kapadia and Zekhnini (2019) does separate jumps into positive and negative ones.

tion 3 discusses the data and main results. Section 4 explores the economic channel of the predictability by relating the predictive power of the jump factors to the tightness of the short-sale constraint. Section 5 presents robustness tests and Section 6 concludes.

2 Latent Jump Factors by Partial Least Squares

In this section, we present the partial least squares (PLS) approach to estimate time-varying latent jump factors for stocks. We perform estimation for downward and upward jumps separately, which we generically denote by D and U, respectively. Since the methodology works the same regardless of the direction of jumps, the discussion below will be mainly based on downward jumps for brevity. The analyses for upward jumps are parallel.

2.1 A Latent Factor Model

Consider N stocks indexed by $i = 1, 2, \ldots, N$ with traded options available at the end of month t. Let $P^D_{i,t+1}$ stand for the probability of a downward jump of stock i in month $t+1$. We define the best predictor of downward jumps for stock i as of month t, $q^D_{i,t}$, as the conditional expectation of the downward jump probability in the following month given the current information, i.e.,

$$q^D_{i,t} = \mathrm{E}\left[P^D_{i,t+1} | \mathcal{F}_t\right],$$

where $\mathcal{F}_t$ represents the set of available information as of month t. Equivalently, $P^D_{i,t+1}$ can be expressed as

$$P^D_{i,t+1} = q^D_{i,t} + \varepsilon^D_{i,t+1}, \tag{1}$$

where $\mathrm{E}\left[\varepsilon^D_{i,t+1} | \mathcal{F}_t\right] = 0$. Since $q^D_{i,t}$ cannot be directly observed, we call it a latent downward jump factor.

Suppose that for each stock, we observe A different moneyness-maturity combinations for the option-implied volatility (IV), with, $a = 1, 2, \ldots, A$. We assume that in month t the IV of each stock i at each moneyness-maturity combination a, $IV_{i,t,a}$, is linearly related to the latent downward jump factor through

$$IV_{i,t,a} = c_{t,a} + \pi_{t,a} q_{i,t}^{D} + e_{i,t,a}, \tag{2}$$

where $c_{t,a}$ is a constant intercept, $\pi_{t,a}$ measures the sensitivity of $IV_{i,t,a}$ with respect to $q_{i,t}^{D}$, and $e_{i,t,a}$ is an error term with a zero mean.

Two remarks are worth noting here. First, Eq. (2) indicates that the latent downward jump factor, $q_{i,t}^{D}$, is a common driving force of IVs at different moneyness-maturity combinations. Nevertheless, it does not assert that $q_{i,t}^{D}$ is the only common determinant of IVs at different positions. There can be other common factors, which are all encapsulated in the error term, $e_{i,t,a}$. Second, for any specific moneyness-maturity combination a, the sensitivity parameter, $\pi_{t,a}$, is assumed to be the same across all stocks. This says that the IVs respond to the latent downward jump factor in the same way for all stocks. This allows us to estimate the relation between the IVs and downward jumps using information in the cross section of stocks.

2.2 Partial Least Squares Estimation

While the latent downward jump factor is unobservable, it manifests itself through the observable IVs. If we view the IV at each moneyness-maturity position as a separate variable, then recovering the latent downward jump factor from the IVs essentially calls for extracting a common driving factor from IVs at various positions. A widely used approach to solving such tasks is the principal component analysis (PCA), which aims to extract common information from a large set of variables. However, a potential problem is that as mentioned earlier, the latent downward jump factor is unlikely to be the only common determinant, and probably not even the most important common factor, of IVs at different positions. If we were to use the PCA approach to obtain the first few principal components, we likely end up with some common driving factor that might not be related to downward jumps.

How do we ensure that the common factor we obtain from an econometric procedure exactly captures the propensity of downward jumps? This can be accomplished by the PLS approach. Like the PCA, the PLS approach also aims to extract common driving forces from a large cross section of variables. Unlike the PCA which does so based on the correlation among the predictors only, the PLS approach extracts common information in the predictors that is the most relevant for the prediction of the target variable, which in our case is the likelihood of downward jumps.

The most intuitive estimation procedure of the PLS approach consists of two stages, and it can be performed out of sample. In particular, to predict the jump probabilities at month $t+1$, we use data collected during months $t-1$ and t. The two stages described below illustrate how to estimate the stock jump factors for month $t+1$.

2.2.1 First Stage

In the first stage, for each moneyness-maturity combination a, we regress the IVs observed in month $t-1$ on a dummy variable representing downward jump realizations in month t across all stocks, i.e.,

$$IV_{i,t-1,a} = \gamma_{t-1,a} + \lambda_{t-1,a} 1^D_{i,t} + \theta_{i,t-1,a}, \quad a = 1, \cdots, A,$$

where $1^D_{i,t}$ equals one if stock i experiences a downward jump in month t and zero otherwise. We run A such regressions, one for each moneyness-maturity combination a.

The idea of the first stage can be understood in relation to the latent factor model in Eq. (2). If we rewrite Eq. (2) for month $t-1$, we obtain,

$$IV_{i,t-1,a} = c_{t-1,a} + \pi_{t-1,a} q^D_{i,t-1} + e_{i,t-1,a}.$$

Utilizing the assumption that the sensitivity parameter, $\pi_{t-1,a}$, is constant across stocks, we can estimate it using cross-sectional regressions. Since the latent downward jump factor, $q^D_{i,t-1}$, is unobservable, we regress $IV_{i,t-1,a}$ on some proxy of $q^D_{i,t-1}$. Here we choose the downward jump dummy in the following month, $1^D_{i,t}$, as such a proxy. The choice of this proxy is natural, because according to (1), a higher value of $q^D_{i,t-1}$ increases the probability of realized downward jumps in the subsequent month. Based on this, the resulting slope coefficient, $\widehat{\lambda}_{t-1,a}$, can be viewed as an estimator of $\pi_{t-1,a}$. This thus enables us to extract the relation between the IVs and the likelihood of downward jumps.

2.2.2 Second Stage

In the second stage of the PLS approach, for each stock i, we regress the IVs observed in month t on the estimated $\widehat{\lambda}_{t-1,a}$ from the first stage, across all moneyness-maturity combinations, i.e.,

$$IV_{i,t,a} = \delta_{i,t} + DJF_{i,t}\widehat{\lambda}_{t-1,a} + \eta_{i,t,a}, \quad i = 1, \cdots, N.$$

We run a total of N such regressions, one for each stock i. The use of $\widehat{\lambda}_{t-1,a}$ makes sure that all information required to perform these regressions, in particular the downward jump realizations in month t needed to estimate $\widehat{\lambda}_{t-1,a}$ in the first stage, is available as of the time when predicting downward jumps for month $t+1$. Therefore, the resulting slope coefficient, $\widehat{DJF}_{i,t}$, is an out-of-sample estimator of the latent downward jump factor, $q^D_{i,t}$, and hence can be used for prediction.

Again, the second stage can be understood in relation to the laten factor model in Eq. (2). Since $\pi_{t,a}$ is not obtainable, we implicitly assume that $\pi_{t,a} = \pi_{t-1,a}$, and use $\widehat{\lambda}_{t-1,a}$ to proxy for $\pi_{t-1,a}$. Intuitively, this assumption states that the relation between the IVs and the latent downward jump factor is persistent over time. This assumption enables us to predict stock returns in month $t+1$ with information available at the end of month t. Next, we turn to examining the empirical performance of our methodology.

3 Empirical Analysis of The Predictive Power of Jump Factors

In this section, we estimate the downward and upward jump factors using the PLS approach for a large set of options on common stocks and explore their information content for the prediction of jumps and stock returns.

3.1 Data, Sample, and Summary Statistics

Our sample period is from January 1996 to December 2017. We obtain monthly data on the IV surface of all common stocks available in OptionMetrics, which covers wide ranges of moneyness and maturity levels. In particular, on each date and for each stock, IVs with deltas of ± 0.20, ± 0.25, ± 0.30, ± 0.35, ± 0.40, ± 0.45, ± 0.50, ± 0.55, ± 0.60, ± 0.65, ± 0.70, ± 0.75, and ± 0.80 (positive deltas for call options and negative deltas for put options) and expirations of 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days are available. This gives rise to 260 different moneyness-maturity combinations. The IV surface is estimated in OptionMetrics for a stock on a given date using a methodology based on kernel smoothing only if there are enough option price data to accurately interpolate the required values. As a result, stocks that are very thinly traded on the options market are automatically dropped. In addition, we also obtain monthly stock returns from CRSP.

Our sample includes all the stocks that have available IV surface data. Table 1 reports the summary statistics of firm characteristics of the stocks in our sample. We have around 6500 stocks. As all the stocks under consideration have liquidly traded options, they are relatively big stocks, with an average size of \$3.89 billion.[3] The average book-to-market ratio, profitability, investment and illiquidity are 0.57, 0.0067, 0.25, and 0.0158, respectively.[4]

[3]Firm size is the year-end market capitalization for the preceding fiscal year.

[4]Book-to-market is the ratio of the book value of equity to market capitalization as of the end of the preceding fiscal year. Firm profitability is measured following Hou, Xue, and Zhang (2015) as income before extraordinary items for the calendar year preceding the month of interest divided by one-quarter-lagged

We define a downward (upward) jump for a stock as a monthly stock return below (above) a certain threshold. For our main analyses, we use -15% as the downward jump threshold and 15% as the upward jump threshold. For robustness, we also repeat our analyses based on milder thresholds of $\pm 10\%$ and more extreme ones of $\pm 20\%$. As reference points, the 5^{th}, 10^{th}, and 25^{th} percentiles of monthly stock returns over the sample period are -22%, -15%, and -6%, and the 75^{th}, 90^{th}, and 95^{th} percentiles are 6%, 15%, and 25%, respectively. Hence, the jump thresholds chosen for our analyses represent relatively large stock price movements in both directions.

3.2 Information Content of the Jump Factors

We now examine the information content of the PLS jump factors regarding future probabilities of jumps and stock returns. We address this question using the portfolio-sorting approach. At the end of each month, we sort stocks into deciles by the estimated DJF, and we track the realized probabilities of downward and upward jumps as well as the returns from different decile portfolios in the following month.

The results are displayed in Figure 1 (based on a downward jump threshold of -15%) and Table 2 (based on downward jump thresholds of -10%, -15%, and -20%). One can see that for all jump thresholds, there is a positive relation between the DJF and the realized probability of downward jumps. In particular, the downward jump probabilities of the bottom and top deciles sorted by the DJF estimated based on a jump threshold of -15% are 11.00% and 17.00%, respectively. On the other hand, the realized probability of upward jumps does not seem to have a clear relation with the DJF. Based on a downward jump threshold of -15%, the bottom and top deciles have similar upward jump probabilities of

book equity. Firm investment is measured following Hou, Xue, and Zhang (2015) as the annual change in total assets for the calendar year preceding the month of interest scaled by one-year-lagged total assets. Amihud (2002) illiquidity is estimated as the average absolute daily return over daily trading volume during the calendar year that precedes the month of interest, scaled by the CRSP cross-sectional average of this illiquidity measure.

13.62% and 15.89%, respectively. This suggests that our DJF can separate the tendency of downward jumps from the likelihood of upward jumps.

The average stock return has a clear inverse relation with the DJF, consistent with the fact that stocks in higher deciles are more likely to experience crashes. Based on a downward jump threshold of −15%, the average monthly returns of the bottom and top deciles are 1.39% and −0.41%, respectively, which are significantly different at the 1% level based on Newey-West standard errors.[5] Taking a long position in the bottom decile and a simultaneous short position in the top decile would yield an annualized return of 18.36% (1.53%×12) and an annualized Sharpe ratio of 1.29. The risk-adjusted alpha of the long-short portfolio is economically large and statistically significant at the 1% level after accounting for the Fama and French (2016) five factors (market, size, value, profitability, and investment), the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003).[6] This abnormal return comes from both the long and the short positions. Hence, we can identify stocks that are the most likely to experience a downward jump by analyzing the past relation between the IVs and downward jumps and applying this relation forward.

We then repeat our analysis for the PLS upward jump factor (UJF). The prediction performance turns out to be less successful. As shown in Figure 2 and Table 3, the relation between the UJF and the realized probability of upward jumps is weak in terms of economic magnitude. More importantly, the realized probability of downward jumps also tends to move in almost the same pattern with the UJF. For example, based on an upward jump threshold of 15%, the realized upward jump probabilities of the bottom and top deciles are 13.17% and 16.18%, with a small difference of 3.00%. The realized downward jump probabilities of the bottom and top deciles are 12.43% and 15.11%, respectively, with a difference of

[5]Following Stock and Watson (2011, pg. 599), we choose the number of lags for the Newey-West test based on the rule of thumb:

$$L = 0.75T^{1/3},$$

where L is the number of lags used and T is the number of observations in the time series.

[6]We obtain the Fama-French five factors from Kenneth French's online data library and the momentum and liquidity factors from WRDS.

2.68%. This indicates that the likelihood of upward and downward jumps moves in almost indistinguishable patterns with the UJF. In other words, the UJF is incapable of separating upward jumps from downward ones. Consistent with this, there is no clear pattern between the UJF and the future stock returns.

In sum, our findings show that option prices can forecast downward jumps with a reasonable confidence level, but they cannot forecast upward jumps. Thus, we will focus on the performance of the DJF estimated based on jump thresholds of -15%, but using other thresholds do not change our main results.

3.3 Source of Information

So far we have shown that the PLS jump factors estimated from option prices contain forward-looking information useful for the prediction of downward jumps, but not upward jumps. Since the DJF is estimated using IVs at all moneyness-maturity positions, a natural question is whether some positions contain more information than others on the likelihood of downward jumps. In particular, we are interested in exploring the source of information along two dimensions. The first is whether the information content is affected by whether we use call or put options for our estimation. The second is whether the information content is affected by the time to maturity of the IVs used for estimation. Below we address these two questions.

3.3.1 Call vs. Put

An investor with information on a future downward jump of a stock can potentially make a profit from two option trading strategies, writing a call or buying a put. These are also the two possible channels through which information on a future downward jump can get incorporated into current option prices. Which one of the two channels is more effective for the expression of bearish opinions? Presumably, a more effective channel of information should give rise to more informative prices of the corresponding options. Along this line, we re-estimate the out-of-sample DJF by using only call options or only put options, and compare their predictive power.

Table 4 reports the findings. We start by estimating the DJF using IVs of call options only. The results are disappointing. Although the realized probability of downward jumps is generally increasing in the DJF, the realized probability of upward jumps follows very similar trend. In particular, the downward jump probabilities of the bottom and top deciles are 10.41% and 15.34% with a difference of 4.94%, and the upward jump probabilities of the two deciles are 12.33% and 16.37% with a difference of 4.05%. This means that the DJF estimated using only call options cannot distinguish the likelihood of downward jumps from that of upward ones. In addition, the relation between the DJF and the stock return is also unclear. We do not have a monotonic relation, and the return difference between the extreme deciles is not statistically significant. This means that call option prices alone do not provide sufficient information for the prediction of downward jumps.

We then estimate the DJF using IVs of put options only. The results are improved to some extent. The realized downward jump probability is higher for the top decile than for the bottom decile by 5.27%, whereas the realized upward jump probability is higher for the top decile than for the bottom decile by only 3.23%. This shows that the DJF estimated this way has some ability to separate the tendency of downward jumps from that of upward ones. The portfolio return also has a decreasing trend with the DJF, although the difference mainly comes from higher deciles. A zero-investment strategy with a long position in the bottom decile and a short position in the top decile earns a statistically significant annualized return of 10.46% (0.87% $\times$ 12) and an annualized Sharpe ratio of 0.87. The alpha of the strategy is also significantly positive at the 1% level. This indicates that put option prices alone contain information for the prediction of downward jumps.

Overall, our results show that prices of put options contain more information than those of call options for the forecast of downward jumps. This suggests that buying put options is a more effective channel than writing call options for the incorporation of negative information into option prices. Somewhat surprisingly, if we compare the results from using put options alone and the earlier results from using call and put options together (Section 3.2), we see that the DJF estimated using both has stronger predictive power and leads to strategies with better performance. One possible explanation is that even though call option prices alone do not contain much information on downward jumps, they serve to provide a benchmark against which information in put option prices can be better revealed. This is also consistent with the previous literature using the difference of the put and call options to predict stock returns.

3.3.2 Long vs. Short Maturity

We use a prediction horizon of one month for our analyses. Given this, one would expect that prices of options with exactly one month to maturity should contain the most relevant information for the prediction of jumps and returns over this horizon, and that options with longer maturity may not provide additional information. We wonder if this is the case. To this end, we re-estimate the DJF separately using IVs with 30 days to maturity and IVs with more than 30 days to maturity and examine their respective predictive power.

The results are reported in Table 5. We start by estimating the DJF using only IVs with 30 days to maturity. After sorting stocks into deciles based on this estimate, we see that the probability of subsequent downward jumps has a rising trend. The probabilities for the bottom and top deciles are 10.80% and 14.33%, respectively. On the other hand, the realized upward jump probability does not seem to have a clear relation with the DJF. The probabilities for the bottom and top deciles are 13.70% and 14.12%, which are very close to each other. In addition, the stock return significantly decreases as the DJF becomes higher. A long-short strategy based on the extreme deciles earns an annualized return of 13.43% (1.12% $\times$ 12), a significantly positive alpha, and an annualized Sharpe ratio of 1.14. These findings confirm that IVs with 30 days to maturity alone do contain information on the likelihood of downward jumps in the next month, as expected.

What is less expected is that the DJF based on IVs with more than 30 days to maturity yields even better performance. The realized downward jump probability of the top decile is higher than that of the bottom decile by 6.26%. In comparison, the upward jump probability of the top decile is only higher than that of the bottom decile by 2.38%. The portfolio return also decreases significantly with higher DJF values. A long-short strategy based on the extreme deciles earns an annualized return of 18.88% (1.573% $\times$ 12) and an annualized Sharpe ratio of 1.33. These numbers are close to the baseline results obtained using IVs of all maturity levels.

Our findings show that prices of options maturing in more than one month contain more information on downward jumps and returns over the following month than prices of options maturing in exactly one month. This might be counterintuitive at first thought, but there is a reason behind this. In fact, all stock options examined in our sample are American options, which can be exercised prior to expiration. As a result, the "effective" maturity of an option is indeed shorter than the stated maturity. Because of this, prices of options with more than one month to maturity can potentially provide incremental information on the prospect of the underlying stocks in the next month that is not already reflected in the prices of one-month options.

3.4 Controlling for Other Characteristics

We have shown that the DJF estimated out of sample negatively predicts future stock returns. We ask whether this relation could be explained by other variables that have been documented in the literature. We examine two sets of variables. The first set includes firm and stock characteristics, and the second set includes option-related characteristics.

The literature has proposed hundreds of variables capturing various firm fundamentals and stock characteristics that predict stock returns. Green, Hand, and Zhang (2017) identify

12 characteristics that provide independent information on future stock returns by examining 94 characteristics simultaneously. We focus on these 12 firm and stock characteristics for our analysis.

- Book-to-market (bm): Proposed by Rosenberg, Reid, and Lanstein (1985), and defined as the book value of equity divided by the market capitalization.

- Cash holdings ($cash$): Proposed by Palazzo (2012), and defined as cash and cash equivalents divided by the average total assets.

- Change in 6-month momentum (Δmom): Proposed by Gettleman and Marks (2006), and defined as the cumulative return from month $t-6$ to month $t-1$ minus that from month $t-12$ to month $t-7$.

- Change in number of analysts ($\Delta nanalyst$): Proposed by Scherbina (2007), and defined as the change in the number of analyst forecasts from month $t-3$ to month t.

- Earnings announcement return (ear): Proposed by Brandt, Kishore, Santa-Clara, and Venkatachalam (2008), and defined as the sum of daily returns in the three-day window around earnings announcement.

- One-month momentum ($mom1m$): Proposed by Jegadeesh and Titman (1993), and defined as the cumulative return over the previous month.

- Number of earnings increases ($nincr$): Proposed by Barth, Elliott, and Finn (1999), and defined as the number of consecutive quarters (up to eight quarters) with an increase in the earnings over the same quarter in the prior year.

- R&D to market capitalization ($rdmve$): Proposed by Guo, Lev, and Shi (2006), and defined as the R&D expense divided by the market capitalization.

- Return volatility ($retvol$): Proposed by Ang, Hodrick, Xing, and Zhang (2006), and defined as the standard deviation of daily returns from the previous month.

- Share turnover (*turn*): Proposed by Datar, Naik, and Radcliffe (1998), and defined as the average monthly trading volume for the most recent three months scaled by the number of shares outstanding in the current month.

- Volatility of share turnover (*turnvol*): Proposed by Chordia, Subrahmanyam, and Anshuman (2001), and defined as the standard deviation of daily share turnover in the previous month.

- Zero trading days (*zerotrade*): Proposed by Liu (2006), and defined as the number of zero-trading days over the previous month. Because our sample covers stocks with traded options, these stocks are in general large and liquid for which *zerotrade* mostly takes a zero value. Due to the lack of variation in *zerotrade*, we drop it from our main analysis, but including this variable does not change our results.

Option-related variables that have been documented to predict stock returns include two classes. One class of variables is based on the IVs.

- Implied volatility slope/skewness (*ivs*): Xing, Zhang, and Zhao (2010) define *ivs* as the difference between the at-the-money call IV (delta of 0.5) and the out-of-the-money put IV (delta of −0.2) both with 30 days to maturity, and they show that *ivs* positively predicts future stock returns. Yan (2011) defines *ivs* in a slightly different way as the difference between at-the-money call IV (delta of 0.5) and at-the-money put IV (delta of −0.5). We adopt the definition of Xing, Zhang, and Zhao (2010) for our analysis, but using the definition of Yan (2011) does not affect our results.

- Volatility spread (*vsp*): Bali and Hovakimian (2009) define *vsp* as the difference between the realized and the implied stock return volatility, where the realized volatility is computed as the annualized standard deviation of daily stock returns over each month, and the implied volatility is taken as the average of the at-the-money call and put IVs (deltas of ± 0.5) with 30 days to maturity. They find that higher *vsp* predicts lower stock returns.

- Implied volatility innovations (Δciv and Δpiv): An, Ang, Bali, and Cakici (2014) define Δciv and Δpiv as the changes from one month to the next in the at-the-money call IV (delta of 0.5) and the at-the-money put IV (delta of -0.5), respectively, both with 30 days to maturity. They find that stocks with large Δciv (Δpiv) tend to have higher (lower) future returns.

The other class of option-related characteristics is based on the option volume (Stephan and Whaley, 1990; Amin and Lee, 1997; Easley, O'Hara, and Srinivas, 1998; Chan, Chung, and Fong, 2002; Cao, Chen, and Griffin, 2005; Pan and Poteshman, 2006; Johnson and So, 2012).

- Option to stock volume ratio (*osvolume*): Following Johnson and So (2012), we define *osvolume* as the ratio of the total option market volume (aggregated across calls and puts) to the total equity market volume during the previous month. Johnson and So (2012) show that *osvolume* negatively predicts stock returns.

- Call to put volume ratio (*cpvolume*): Following Pan and Poteshman (2006), we define *cpvolume* as the ratio of the total trading volume of calls over the total trading volume of puts during the previous month. Pan and Poteshman (2006) show that *cpvolume* positively predicts stock returns.

- Call to put open interest ratio (*cpoi*): Following An, Ang, Bali, and Cakici (2014), we define *cpoi* as the ratio of the total open interest of calls over the total open interest of puts.

Since different variables have different units and scales, we standardize our estimated out-of-sample jump factors and other characteristics in each month to allow for easier interpretation.

We start by examining the correlations among different characteristics. Table 6 reports the pairwise correlation coefficients of our jump factors and the firm/stock characteristics. The firm and stock characteristics are in general only weakly correlated with our DJF. In particular, the characteristic that is most strongly correlated with the DJF is the return volatility, *retvol*, which has correlation coefficients of 0.1462. This is intuitive, because the jump factors are estimated based on the IVs, which are considered to capture the expected volatility of the underlying stocks.

Table 7 reports the pairwise correlations of our DJF and other option-related variables. The correlations are generally stronger between DJF and the IV related variables, which is expected. For example, the DJF has a negative correlation of -0.3237 with the IV slope, ivs, and a positive correlation of 0.2556 with the put IV innovation, Δpiv. However, the correlations between DJF and the volume related variables are virtually zero.

We are particularly interested in whether these characteristics drive the relation between our DJF and future stock returns. To see this, we conduct the Fama and MacBeth (1973) regressions. In each month t, we cross-sectionally regress the stock return on the DJF estimated for month $t-1$, controlling for lagged values of other characteristics, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t} DJF_{i,t-1} + characteristics_{i,t-1} + \phi_{i,t}.$$

Table 8 reports the average slope coefficients from the Fama-MacBeth regressions. Since all variables are standardized, the reported coefficients can be conveniently interpreted as the average change in the stock return for each one-standard-deviation increase in the corresponding characteristic variable. We start by using the DJF as the only explanatory variable in the regression. The coefficient is negative and significant at the 1% level. In particular, increasing the DJF by one standard deviation reduces future stock returns by 0.44% per month on average. This strong negative relation is consistent with our portfolio sorting results. Interestingly, controlling for the firm and stock characteristics has the biggest impact, slightly reducing (in magnitude) the coefficient to -0.0038, while controlling for the option characteristics actually increases (in magnitude) the coefficient to -0.0049, in spite of the sizable correlations of these variables with the DJF. Finally, controlling for all the firm, stock, and option characteristics barely affects the results; the coefficient of the DJF changes slightly from -0.0044 to -0.0043. This confirms that the predictive power of the DJF cannot be explained by these characteristics, even if some of them have nontrivial correlations with the DJF. In addition, when all characteristics are included simultaneously in the regression, only seven control variables remain significant at the 10% level. Specifically, the stock return increases with higher values of the earnings announcement return (ear), R&D to market capitalization ($rdmve$), IV slope (ivs), and call to put volume ratio ($cpvolume$), and it decreases with higher values of the one-month momentum ($mom1m$), volatility spread (vsp), and option to stock volume ratio ($osvolume$). More interestingly, the coefficients of these variables ranges between -0.0020 for $mom1m$ and 0.0030 for $rdmve$, all being much smaller in magnitude than that of the DJF. This suggests that the DJF not only provides information on future stock returns independent from that reflected in other characteristics, its predictive power is also stronger than any of these characteristics.

4 Predictive Power of Jump Factors and Short-Sale Constraint

We have learned that the DJF can predict future downward jumps, but the UJF fails to predict future upward jumps. Why are downward jumps more predictable than upward jumps based on information reflected in option prices? One possible explanation is that short investors generally face trading constraints in the equity market, whereas long investors do not. The existence of options essentially loosens the short-sale constraint faced by informed investors by providing them with an alternative trading channel to profit from negative information. This allows negative information to be more effectively incorporated into option prices than positive information, thus leading to better predictability of downward than upward jumps.

If the above economic force is in effect, we would expect the DJF to perform better in identifying downward jumps among stocks with tighter short-sale constraint. Below we test this hypothesis in three different ways. First, we use the short interest as a proxy of the short-sale constraint. Second, we use institutional holding to measure the tightness of short-sale constraint. Finally, we exploit the Pilot Program of Regulation SHO as a quasi-experiment to examine the effect of loosening the short-sale constraint on the predictive power of our estimated jump factors.

4.1 Short Interest

We start by measuring the tightness of the short-sale constraint using the logarithm of the ratio of short interest over the total number of shares outstanding, which we denote by *shortint*.[7] Intuitively, a higher short interest ratio implies fewer borrowable shares available, which imposes a constraint on investors demand to short sell. The short interest data are from Compustat, and the number of shares outstanding can be obtained from CRSP. Since the short interest data are missing for about half of our sample stocks before July 2003, we use the period from July 2003 to December 2017 for the current analysis.

We apply a regression approach to test our hypothesis. Let $shortintH_{i,t}$ denote the high short interest ratio dummy that equals one if the short interest ratio, $shortint_{i,t}$, for stock i in month t is higher than the median value of short interest ratios for all stocks in that month. For each month t, we cross-sectionally regress the stock return on the lagged values

[7]We take the logarithm of the short interest ratio, because this ratio is extremely right-skewed in the cross-section.

of the DJF, the high short interest ratio dummy, and their interaction, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t}DJF_{i,t-1} + b_{2,t}shortintH_{i,t-1} + b_{3,t}DJF_{i,t-1} \times shortintH_{i,t-1} + \phi_{i,t}, \quad (3)$$

where $DJF_{i,t-1}$ is standardized in each month to have zero mean and unit variance. If our hypothesis holds true, we expect the coefficient on the interaction term, $b_{3,t}$, to be negative on average. This would mean that the negative relation between the DJF and the future stock return is stronger for stocks with higher short interest ratios.

Table 9 displays the results. The coefficient on the DJF takes a significantly negative value of -0.0024, meaning that for stocks with lower-than-median short interest ratios, a one-standard-deviation increase in the DJF predicts a 0.24% decrease in the monthly stock return. The coefficient on the short interest ratio dummy is also significantly negative, implying that on average stocks with higher short interest ratios deliver lower future returns. Most interestingly, the coefficient on the interaction term is significantly negative with a value of -0.0030. This means that for stocks with higher-than-median short interest ratios, increasing the DJF by one standard deviation would lead to an additional decrease of 0.30% in the monthly return relative to stocks with lower-than-median short interest ratios. Equivalently, for stocks with high short interest ratios, a one-standard-deviation increase in the DJF on average predicts a 0.54% (0.24% + 0.30%) decrease in the monthly stock return.

We also run the regression (3) by replacing the high short interest ratio dummy with the actual short interest ratio level, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t}DJF_{i,t-1} + b_{2,t}shortint_{i,t-1} + b_{3,t}DJF_{i,t-1} \times shortint_{i,t-1} + \phi_{i,t}, \quad (4)$$

where both $DJF_{i,t-1}$ and $shortint_{i,t-1}$ are standardized for each month. As shown in the table, the coefficients on both the DJF and the short interest ratio are negative, suggesting that stocks with higher DJF values and higher short interest ratios earn lower returns.

Furthermore, the interaction term again has a significantly negative coefficient, confirming that the negative relation between the DJF and the future stock return is significantly stronger for firms with higher short interest ratios.

In sum, we have found that the DJF performs better in predicting downward jumps when the short interest ratio is higher. This is consistent with our expectation that negative information being more effectively incorporated into option prices when the short-sale constraint is more binding. Hence, options relax the short-sale constraint that investors face in the equity market by providing them with an alternative trading channel to profit from negative information.

4.2 Institutional Holding

Following Berkman, Dimitrov, Jain, Koch, and Tice (2009), we use the institutional holding ratio as a second proxy of the tightness of the short-sale constraint. The idea is that institutional investors such as mutual funds are the major lenders of stock shares, and institutional investors typically face barriers of short sales themselves. As a result, firms with high institutional holding generally have less binding short-sale constraint.[8] We define the institutional holding ratio, *insthold*, as the ratio of the number of shares held by institutional investors to the total number of shares outstanding. The institutional holding data are obtained from the Thomson Reuters Institutional (13f) Holdings file.

Let $insthold L_{i,t}$ denote the low institutional holding dummy that equals one if the institutional holding ratio, $insthold_{i,t}$, for stock i in month t is lower than the median value of institutional holding ratios for all stocks in the month. In each month t, we cross-sectionally regress the stock return on the lagged values of the DJF, the low institutional holding dummy,

[8] See, for example, Chen, Hong, and Stein (2002), DAvolio (2002), Ali, Hwang, and Trombley (2003), Almazan, Brown, Carlson, and Chapman (2004), Asquith, Pathak, and Ritter (2005), and Nagel (2005).

and their interaction, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t}DJF_{i,t-1} + b_{2,t}instholdL_{i,t-1} + b_{3,t}DJF_{i,t-1} \times instholdL_{i,t-1} + \phi_{i,t}, \quad (5)$$

where $DJF_{i,t-1}$ is standardized in each month to have zero mean and unit variance. If our hypothesis holds true, we expect the coefficient on the interaction term, $b_{3,t}$, to be negative on average. This would mean that the negative relation between the DJF and the future stock return is stronger for stocks with tighter short-sale constraint as characterized by lower institutional holding.

Table 10 reports the results. The coefficient on the DJF takes a significantly negative value of -0.0027, meaning that for stocks with higher-than-median institutional holding, a one-standard-deviation increase in the DJF predicts a 0.27% decrease in the monthly stock return. More importantly, the coefficient on the interaction term, $b_{3,t}$, is also significantly negative with a value of -0.0016. This means that for stocks with lower-than-median institutional holding, increasing the DJF by one standard deviation would lead to an additional decrease of 0.16% in the monthly return relative to stocks with higher-than-median institutional holding. Equivalently, for stocks with low institutional holding, a one-standard-deviation increase in the DJF on average predicts a 0.43% $(0.27\% + 0.16\%)$ decrease in the monthly stock return.

We then repeat the regression (5) by replacing the low institutional holding dummy with the actual institutional holding level, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t}DJF_{i,t-1} + b_{2,t}insthold_{i,t-1} + b_{3,t}DJF_{i,t-1} \times insthold_{i,t-1} + \phi_{i,t}, \quad (6)$$

where both $DJF_{i,t-1}$ and $insthold_{i,t-1}$ are standardized for each month. As shown in the table, the coefficient on the DJF is significantly negative as before, suggesting that stocks with higher DJF values earn lower returns. Furthermore, the coefficient on the interaction terms,

$b_{3,t}$, is now significantly positive, confirming that the negative relation between the DJF and future stock returns is significantly stronger for firms with lower institutional holding.

In sum, we have found that the DJF performs better in predicting future stock returns when institutional holding is lower. Again, this is consistent with that negative information is more effectively incorporated into option prices when the short-sale constraint is tighter.

4.3 Quasi-Experiment: Pilot Program of Regulation SHO

The two proxies we used above for the tightness of the short-sale constraint, the short interest ratio and the institutional holding ratio, are subject to endogeneity concerns. To address such issues, we now exploit the Pilot Program of Regulation SHO from 2005 to 2007 as a quasi-experiment to examine the relation between the short-sale constraint and the information content of our PLS jump factor.

Prior to Regulation SHO, stocks traded on NYSE/AMEX were subject to the uptick rule, which allowed short sales to be placed only on a plus tick or a zero-plus tick. Stocks traded on Nasdaq were subject to the bid price test, which prohibited short sales at or below the inside bid when the inside bid was at or below the previous inside bid. Regulation SHO was designed by the SEC to investigate how such short-sale constraint affects market quality. The Pilot Program of Regulation SHO targeted Russell 3000 constituent stocks as of June 2004. For stocks in the Russell 3000 index, the Pilot Program designated every third stock ranked by average daily trading volume on NYSE, AMEX, and Nasdaq separately as pilot stocks. The uptick rule and the bid price test were then removed on the group of pilot stocks. The pilot program started on May 2, 2005 and ended on August 6, 2007. However, on July 6, 2007 the SEC removed short-sale price tests for all exchange-listed stocks. Hence, the Pilot Program effectively lasted from May 2, 2005 to July 6, 2007.

We ask whether the predictive power of our estimated downward jump factor is affected differently for pilot and non-pilot stocks by the Pilot Program of Regulation SHO. To answer this question, we use the sample period January 1996 to June 2007 (ending with the Pilot Program). We follow SEC's Securities Exchange Act Release No. 50104 to construct the sets of pilot and non-pilot stocks based on Russell 3000 constituents as of June 2004.[9] We further drop all stocks listed on Nasdaq from our sample and keep stocks listed on NYSE and AMEX only. This is because, as discussed in Diether, Lee, and Werner (2009) and Chu, Hirshleifer, and Ma (2019), the bid price test is not very restrictive, and a large fraction of Nasdaq-listed stock trading is executed on ArcaEx and INET and hence is exempt from the bid price test. As a result, the pilot program has only a small effect on Nasdaq stocks.

We conduct the following triple-difference panel regression:

$$\begin{aligned} ret_{i,t} = \; & b_0 + b_1 DJF_{i,t-1} + b_2 PilotStock_i + b_3 DJF_{i,t-1} \times PilotStock_i \\ & + b_4 DJF_{i,t-1} \times SHOMonth_t + b_5 PilotStock_i \times SHOMonth_t \\ & + b_6 DJF_{i,t-1} \times PilotStock_i \times SHOMonth_t + \eta_t + \phi_{i,t}, \end{aligned} \tag{7}$$

where $DJF_{i,t-1}$ is standardized as before, $PilotStock_i$ is the pilot stock dummy that equals 1 if stock i is a pilot stock and 0 otherwise, $SHOMonth_t$ is the Regulation SHO month dummy which equals 1 if month t is during the pilot program of Regulation SHO (between May 2005 and June 2007) and 0 otherwise, η_t represents time-fixed effects, and standard errors are clustered at the stock level. $SHOMonth_t$ is subsumed by the time-fixed effects, and therefore dropped from the regression. Since the estimation of the lagged downward jump factor, $DJF_{i,t-1}$, uses options prices in month $t-1$ and $t-2$ for any particular month t, we drop the two months at the beginning of the Pilot Program (May and June of 2005) to keep the analysis clean.

Our key coefficient of interest is b_6, which measures the difference-in-difference (DID) of the coefficient on the DJF between pilot and non-pilot stocks during the experiment months. Because the DJF has been shown to negatively predict stock returns and we conjecture that

[9] See https://www.sec.gov/rules/other/34-50104.htm.

stronger predictive power is associated with tighter short-sale constraint, we expect b_6 to be positive. This would mean that during the Pilot Program, the predictive power of the DJF becomes weaker for pilot stocks which are subject to looser short-sale constraints. Table 11 reports the results. The coefficient on the DJF remains significantly negative. Most importantly, b_6 is significantly positive, as expected, confirming that the predictive power of the DJF is significantly weakened for pilot stocks during the pilot program of Regulation SHO.

Overall, our analyses in this section further confirm that the predictive power of the DJF is associated with tighter short-sale constraint in the equity market. Furthermore, there seems to be a causal effect between the short-sale constraint and the predictive power of the DJF.

5 Robustness Tests

In this section, we present robustness tests for our main analyses. First, we test the performance of the PLS methodology in different subperiods. Next, we split the stocks into big, small, and microcap ones to see if our approach is robust against stock size. We also double-sort the stocks controlling for the proxies of the short-sell constraint. In addition, we repeat the analysis for the idiosyncratic jumps. Finally, we investigate the predictive power of the DJF over longer investment horizons. Overall, our methodology is quite robust under different specifications.

5.1 Subperiods

Our first robustness test is to divide the sample period into two subperiods and test the predictive power of the DJF separately. We explore five different subperiods according to market performance, market volatility level, recession indicator, market sentiment, and random assignment, respectively. We repeat the portfolio sorting procedure for each of the subperiods and report the results in Table 12.

Panels A and B examine how the information content of our estimated jump factors is affected by the overall market performance, and the two subperiods correspond to lower-than-median and higher-than-median market returns, respectively. In Panel A, during months of low market returns, the bottom and top deciles have downward jump probabilities of 16.27% and 25.01%, respectively, with a considerable difference of 8.74%. A zero-investment strategy taking a long position in the bottom decile and a short position in the top decile earns an annualized return of 33.52%, a significantly positive alpha, and an annualized Sharpe ratio of 2.72. In contrast, during months of high market returns, the realized downward jump probabilities of the bottom and top deciles are 5.72% and 8.99%, respectively, with a difference of 3.28%, while the portfolio return is nearly flat as the DJF increases from decile 1 (Low) to decile 10 (High). In summary, our results show that the predictive power of the DJF comes solely from periods during which the market performance is poor. This is intuitive, because the major prediction challenge is to distinguish downward jumps from upward ones, both of which lead to high volatility but in different directions. When the market performs poorly, downward jumps are more likely, which makes it easier to identify them. In contrast, when the market has good performance overall, downward jumps become less likely, making it more difficult to identify the corresponding stocks.

Panels C to J reports the performance of the DJF according to other ways to divide the sample period. Overall, the performance of the PLS methodology is quite robust for these subperiods. Decile portfolios sorted by the DJF exhibit a strong rising trend in terms of the realized probability of downward jumps; realized returns also have a corresponding monotonic pattern. The long-short portfolio always has a positive monthly return that is significant at the 1% level. For example, Panels C and D report the performance of the DJF during times with high and low market volatility, respectively. The realized downward jump probability increases from 7.98% (14.01%) to 12.74% (21.27%) according to the level of the DJF when the market volatility is lower (higher) than median, while the realized return decreases from 1.07% (1.70%) to −0.32% (0.04%) as the DJF increases. Under both cases, the long-short portfolio has an economically large average return of 1.39% and 1.66%, respectively, both are significant at the 1% level. The corresponding Sharpe ratios are 2.55 and 1.5, respectively. The abnormal returns are significant at the 1% level as well, contributed from both legs. Results are similar when dividing the sample period by the recession/expansion indicator, market sentiment, or randomly.[10] During each subsample, we obtain long-short portfolios with large and significant average and abnormal returns.

5.2 Size Effect

Fama and French (2008) document that many anomalies are concentrated in microcap stocks, define as stocks with the market cap below the 20^{th} NYSE percentile. The microcap stocks are on average only about 3% of the market cap of the NYSE/AMEX/NASDAQ universe, but they account for about 60% of the total number of stocks. The problem with these stocks is that they are very illiquid and costly to trade, and thus anomalies in microcap stocks are unlikely to be exploitable in the real-world situation. Subsequently, many studies such as Hou, Xue, and Zhang (2015), Hou, Xue, and Zhang (2017), and Green, Hand, and Zhang (2017), exclude microcap stocks. In this subsection, we follow Fama and French (2008) and split our sample of stocks into big, small and microcap subsamples, according to the 20^{th} and 50^{th} percentile of the sizes of the firms that are listed in the New York Stock Exchange in each month, to check if our methodology is robust against firm size. As reported in Section 3.1, the stocks in our sample have liquidly traded options, thus are relatively big stocks. Indeed, about 59% of the stocks are big ones, about 30% are small ones and only 11% of them are microcaps, according to the cut-offs. For each of the subsample, we repeat our main analysis and report the results in Table 13.

[10]The recession indicator is from the website of the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/USREC. The market sentiment is identified by the IV slope of the S&P 500 options.

Panels A, B, and C present the average realized downward jump probabilities, returns, and abnormal returns for each of the deciles sorted by the DJF, for big, small, and microcap stocks, respectively. We can see that the three subsamples perform similarly, with the microcap being actually the weakest. The realized downward jump probability increases from 11.59%, 11.85%, and 12.63% to 16.60%, 16.46%, and 15.52%, and the average realized return decreases from 1.19%, 1.31%, and 1.08% to 0.13%, 0.02%, and 0.20%, for big, small, and microcap stocks, respectively. The long short portfolio has an average return of 1.06%, 1.30% and 0.88%, with a Sharpe ratio of 0.93, 1.18 and 0.76, for the corresponding three subsamples. The abnormal returns are also economically large and statistically significant at the 1% level. Both the long and short end of the portfolio contribute to the abnormal returns.

5.3 Double-Sorted Portfolios

To further identify the information contained in the DJF with that in the short-sale constraint and limit of arbitrage proxies, we conduct sequential double sorts. In particular, we use institutional holding ratio ($insthold_{i,t-1}$) or the short interest ratio ($shortint_{i,t-1}$) as the first sorting variable. At the end of each month, we first sort the stocks into five quintiles based on one of the two measures. Within each quintile, we further sort the stocks into quintiles based on the DJF. Therefore, with double-sorted portfolios, we are able to identify the effect of the DJF after controlling for other relevant measures.

Table 14 reports the average monthly returns of the double-sorted portfolios. We can see that within each quintile sorted by $insthold_{i,t-1}$ or $shortint_{i,t-1}$, the average returns exhibit a largely monotonic decreasing trend as the DJF increases. For example, within quintile 1 sorted by $insthold_{i,t-1}$, the average returns monotonically decrease from 1.32% to -0.31% over the five quintiles sorted by the DJF. When considering the long-short trading strategy, the monthly return monotonically increases (decreases) as the institutional holdings (short interests) increase, ranging from 1.63% (0.61%) to 0.49% (1.45%). The double sort results confirm the previous regression results and provide further evidence that the predictive power of the DJF is associated with the tightness of the short-sale constraint in the equity market.

5.4 Idiosyncratic Jumps

Bégin, Dorion, and Gauthier (2019) and Kapadia and Zekhnini (2019) both argue that idiosyncratic jumps are important determinant of the stock returns. The predictive power of the DJF constructed in Section 3.2 can come from either the jumps from the systematic component of the return, the idiosyncratic component of the return, or both. In this subsection, we examine the predictive power of the DJF using the downward idiosyncratic jumps. We define idiosyncratic return as the residual term from the seven-factor model, and downward idiosyncratic jump as an idiosyncratic return below -15%.

Table 15 reports the results and shows that considering only the idiosyncratic jumps leads to similar results. For example, the difference in the downward jump probabilities is about 5.76% between the top and bottom deciles, similar to the difference in Table 2 (6.01%) when return jumps are used. In addition, the long-short portfolio yields an annual return of 14.88% ($1.24\% \times 12$) and an abnormal return of 12.00%, both significant at the 1% level. The annualized Sharpe ratio is as high as 1.07. As reported in Table 2, the corresponding performance numbers are 18.31% (return), 15.48% (alpha), and 1.29 (Sharpe ratio) when return jumps are used to estimate the DJF. These results suggest that the predictive power of the DJF mainly comes from the idiosyncratic jumps.

5.5 Longer Investment Horizons

In our last robustness check, we evaluate the performance of the DJF-sorted portfolios over longer investment horizons. Table 16 reports the average probabilities of downward jumps, the average returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the DJF over the next three (Panel A), Six (Panel B), Nine (Panel C), and 12 (Panel D) months. Same as in the main analysis, the portfolios are rebalanced monthly based on the DJF available as of the beginning of each month, but they are held for the next few months with overlapping investment horizons.

The results show that the predictive power of the DJF is quite persistent over longer investment horizons. Across all of the horizons being considered, the average downward jump probabilities increase, and the average returns decrease with the increasing of DJF. All of the long-short portfolios have a positive return and a positive abnormal return that are economically large and significant at the 1% level. The Sharpe ratios of these portfolios are 2.04, 2.41, 2.43, and 2.13, respectively.

6 Conclusion

Previous studies suggest that some informed traders trade on the options market to profit from bad news due to the embedded leverage and the lack of the short-sale constraint. In this paper, we seek to answer the following two questions. First, do option prices contain information on the likelihood and direction of jumps in the underlying stock prices? Second, if such information can be identified, does it allow investors to form profitable trading strategies?

We employ the partial least squares (PLS) approach to efficiently extract information about the jumps from the entire IV surface. We refer it as the latent jump factor and test whether it can predict the future realized jump probabilities and returns. We find that option prices have information about the downward jumps but not upward jumps out of sample. In addition, the downward jump factor predicts future stock returns. The spread in returns between the top and bottom deciles in the downward jump factor is 1.53% per month, with a risk-adjusted alpha of 1.29% per month.

We further explore the source of information in the option prices. First, we find that put options alone can predict the downward jump probability and future returns, whereas call options alone cannot. Nevertheless, call options do contribute to predicting the downward jump probability and future returns. Second, both short (one month) and long maturity options contribute to the predictability measured at monthly frequency. Finally, the predictability is robust to a number of firm characteristics and option-related variables that are shown to forecast future stock returns even though many of them are constructed from IVs.

Since informed traders use options to circumvent the short-sale constraint, we would expect stronger predictability for stocks that are subject to tighter short-sale constraint. We use three approaches to test this economic channel, two proxies for the tightness of the short-sale constraint, the short interest and institutional holdings, and one quasi-natural experiment of Regulation SHO, and find consistent evidence supporting this economic channel.

Finally, we show that the predictive power of the downward jump factor is robust to different subperiods and subsamples, to double sorting with the proxies of the short-sale constraint, and to longer investment horizons. Lastly, we use idiosyncratic return jumps instead of return jumps to estimate the downward jump factor and find that the predictive power is mainly driven by the idiosyncratic return jumps.

References

Ali, A., L.-S. Hwang, and M. A. Trombley, 2003, "Arbitrage risk and the book-to-market anomaly," *Journal of Financial Economics*, 69, 355–373.

Almazan, A., K. C. Brown, M. Carlson, and D. a. Chapman, 2004, "Why constrain your mutual fund manager?" *Journal of Financial Economics*, 73, 289–321.

Amihud, Y., 2002, "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets*, 5, 31–56.

Amin, K. I., and C. M. Lee, 1997, "Option trading, price discovery, and earnings news dissemination," *Contemporary Accounting Research*, 14, 153–192.

An, B.-J., A. Ang, T. G. Bali, and N. Cakici, 2014, "The joint cross section of stocks and options," *Journal of Finance*, 69, 2279–2337.

Andersen, T. G., L. Benzoni, and J. Lund, 2002, "An empirical investigation of continuous-time equity return models," *Journal of Finance*, 57, 1239–1284.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The cross-section of volatility and expected returns," *Journal of Finance*, 61, 259–299.

Asquith, P., P. A. Pathak, and J. R. Ritter, 2005, "Short interest, institutional ownership, and stock returns," *Journal of Financial Economics*, 78, 243–276.

Bali, T. G., and A. Hovakimian, 2009, "Volatility spreads and expected stock returns," *Management Science*, 55, 1797–1812.

Bali, T. G., and R. F. Whitelaw, 2014, "Hybrid tail risk and expected stock returns: When does the tail wag the dog?" *Review of Asset Pricing Studies*, 4, 206—-246.

Barth, M. E., J. A. Elliott, and M. W. Finn, 1999, "Market rewards associated with patterns of increasing earnings," *Journal of Accounting Research*, 37, 387–413.

Bates, D. S., 2000, "Post-'87 crash fears in the s&p 500 futures option market," *Journal of Econometrics*, 94, 181–238.

Bégin, J.-F., C. Dorion, and G. Gauthier, 2019, "Idiosyncratic jump risk matters: Evidence from equity returns and options," *Review of Financial Studies*, forthcoming.

Berkman, H., V. Dimitrov, P. C. Jain, P. D. Koch, and S. Tice, 2009, "Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements," *Journal of Financial Economics*, 92, 376–399.

Black, F., 1975, "Fact and fantasy in the use of options," *Financial Analysts Journal*, 31, 36–41.

Black, F., and M. Scholes, 1973, "The pricing of options and corporate liabilities," *Journal of Political Economy*, 81, 637–657.

Bollerslev, T., and V. Todorov, 2011, "Tails, fears, and risk premia," *Journal of Finance*, 66, 2165–2211.

Brandt, M. W., R. Kishore, P. Santa-Clara, and M. Venkatachalam, 2008, "Earnings announcements are full of surprises," Working paper, SSRN eLibrary.

Cao, C., Z. Chen, and J. Griffin, 2005, "Informational content of option volume prior to takeovers," *The Journal of Business*, 78, 1073–1109.

Carhart, M. M., 1997, "On persistence in mutual fund performance," *Journal of Finance*, 52, 57–82.

Chan, K., Y. P. Chung, and W.-M. Fong, 2002, "The informational role of stock and option volume," *Review of Financial Studies*, 15, 1049–1075.

Chapman, D. A., M. F. Gallmeyer, and J. S. Martin, 2018, "Aggregate tail risk and expected returns," *The Review of Asset Pricing Studies*, 8, 36–76.

Chen, J., H. Hong, and J. C. Stein, 2002, "Breadth of ownership and stock returns," *Journal of Financial Economics*, 66, 171–205.

Chernov, M., A. R. Gallant, E. Ghysels, and G. Tauchen, 2003, "Alternative models for stock price dynamics," *Journal of Econometrics*, 116, 225–257.

Chordia, T., A. Subrahmanyam, and V. R. Anshuman, 2001, "Trading activity and expected stock returns," *Journal of Financial Economics*, 59, 3–32.

Chu, Y., D. Hirshleifer, and L. Ma, 2019, "The causal effect of limits to arbitrage on asset pricing anomalies," *Journal of Finance*, Forthcoming.

Datar, V. T., N. Y. Naik, and R. Radcliffe, 1998, "Liquidity and stock returns: An alternative test," *Journal of Financial Markets*, 1, 203–219.

DAvolio, G., 2002, "The market for borrowing stock," *Journal of Financial Economics*, 66, 271–306, Limits on Arbitrage.

Diether, K. B., K. H. Lee, and I. M. Werner, 2009, "It's SHO time! short-sale price tests and market quality," *Journal of Finance*, 64, 37–73.

Easley, D., M. O'Hara, and P. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade," *Journal of Finance*, 53, 431–465.

Eraker, B., M. Johannes, and N. Polson, 2003, "The impact of jumps in volatility and returns," *Journal of Finance*, 58, 1269–1300.

Fama, E. F., and K. R. French, 2008, "Dissecting anomalies," *Journal of Finance*, 63, 1653–1678.

——— , 2015, "A five-factor asset pricing model," *Journal of Financial Economics*, 116, 1–22.

——— , 2016, "Dissecting anomalies with a five-factor model," *Review of Financial Studies*, 29, 69–103.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy*, 81, 607–636.

Gettleman, E., and J. M. Marks, 2006, "Acceleration strategies," Working paper, Seton Hall University.

Green, J., J. R. M. Hand, and X. F. Zhang, 2017, "The characteristics that provide independent information about average u.s. monthly stock returns," *Review of Financial Studies*, 30, 4389–4436.

Guo, R.-J., B. Lev, and C. Shi, 2006, "Explaining the short- and long-term ipo anomalies in the us by r&d," *Journal of Business Finance & Accounting*, 33, 550–579.

Hou, K., C. Xue, and L. Zhang, 2015, "Digesting anomalies: An investment approach," *Review of Financial Studies*, 28, 650–705.

——— , 2017, "Replicating anomalies," Working paper, Ohio State University.

Jegadeesh, N., and S. Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *Journal of Finance*, 48, 65–91.

Jiang, G. J., and T. Yao, 2013, "Stock price jumps and cross-sectional return predictability," *Journal of Financial and Quantitative Analysis*, 48, 1519–1544.

Johnson, T. L., and E. C. So, 2012, "The option to stock volume ratio and future returns," *Journal of Financial Economics*, 106, 262–286.

Kapadia, N., and M. Zekhnini, 2019, "Do idiosyncratic jumps matter?" *Journal of Financial Economics*, 131, 666–692.

Kelly, B., and H. Jiang, 2014, "Tail risk and asset prices," *Review of Financial Studies*, 27, 2841–2871.

Kelly, B., and S. Pruitt, 2013, "Market expectations in the cross-section of present values," *Journal of Finance*, 68, 1721–1756.

——— , 2015, "The three-pass regression filter: A new approach to forecasting using many predictors," *Journal of Econometrics*, 186, 294–316.

Liu, W., 2006, "A liquidity-augmented capital asset pricing model," *Journal of Financial Economics*, 82, 631–671.

Maheu, J. M., and T. H. McCurdy, 2004, "News arrival, jump dynamics, and volatility components for individual stock returns," *Journal of Finance*, 59, 755–793.

Maheu, J. M., T. H. McCurdy, and X. Zhao, 2013, "Do jumps contribute to the dynamics of the equity premium?" *Journal of Financial Economics*, 110, 457–477.

Merton, R. C., 1973, "Theory of rational option pricing," *Bell Journal of Economics and Management Science*, 4, 141–183.

Nagel, S., 2005, "Short sales, institutional investors and the cross-section of stock returns," *Journal of Financial Economics*, 78, 277–309.

Palazzo, B., 2012, "Cash holdings, risk, and expected returns," *Journal of Financial Economics*, 104, 162–185.

Pan, J., 2002, "The jump-risk premia implicit in options: evidence from an integrated time-series study," *Journal of Financial Economics*, 63, 3–50.

Pan, J., and A. M. Poteshman, 2006, "The information in option volume for future stock prices," *Review of Financial Studies*, 19, 871–908.

Pástor, L., and R. F. Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy*, 111, 642–685.

Press, J., 1967, "A compound events model for security prices," *Journal of Business*, 40, 317–335.

Rosenberg, B., K. Reid, and R. Lanstein, 1985, "Persuasive evidence of market inefficiency," *The Journal of Portfolio Management*, 11, 9–16.

Scherbina, A., 2007, “Suppressed negative information and future underperformance,” *Review of Finance*, 12, 533–565.

Stephan, J. A., and R. E. Whaley, 1990, “Intraday price change and trading volume relations in the stock and stock option markets,” *Journal of Finance*, 45, 191–220.

Stock, J. H., and M. W. Watson, 2011, *Introduction to Econometrics*. Pearson, London, UK.

Van Oordt, M. R., and C. Zhou, 2016, “Systematic tail risk,” *Journal of Financial and Quantitative Analysis*, 51, 685–705.

Wold, H., 1966, “Estimation of principal components and related models by iterative least squares,” in *Multivariate Analysis*, ed. by P. Krishnaiaah. Academic Press, New York, pp. 391–420.

——— , 1975, “11 - path models with latent variables: The nipals approach**nipals = nonlinear iterative partial least squares.,” in *Quantitative Sociology*, ed. by H. Blalock, A. Aganbegian, F. Borodkin, R. Boudon, and V. Capecchi. Academic Press, New York, International Perspectives on Mathematical and Statistical Modeling, chap. 11, pp. 307–357.

Xiao, X., and C. Zhou, 2018, “The decomposition of jump risks in individual stock returns,” *Journal of Empirical Finance*, 47, 207–228.

Xing, Y., X. Zhang, and R. Zhao, 2010, “What does the individual option volatility smirk tell us about future equity returns?” *Journal of Financial and Quantitative Analysis*, 45, 641–662.

Yan, S., 2011, “Jump risk, stock returns, and slope of implied volatility smile,” *Journal of Financial Economics*, 99, 216–233.

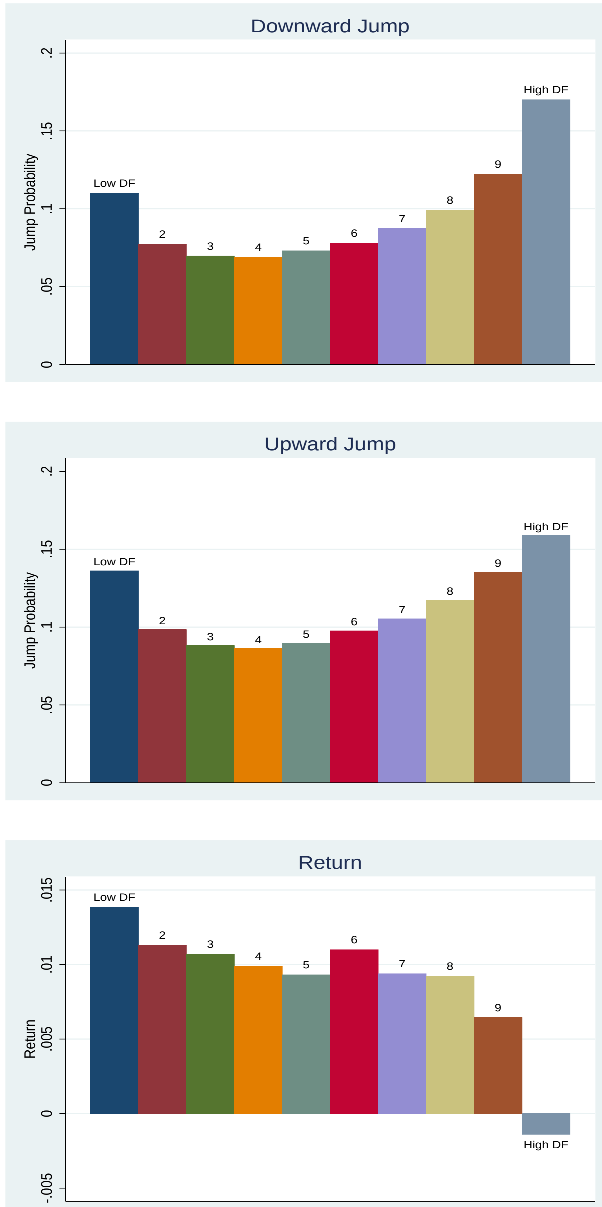

Figure 1: Portfolio Sorts by the Downward Jump Factor
This figure plots the average monthly probabilities of downward and upward jumps as well as the average monthly returns of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15%. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month.

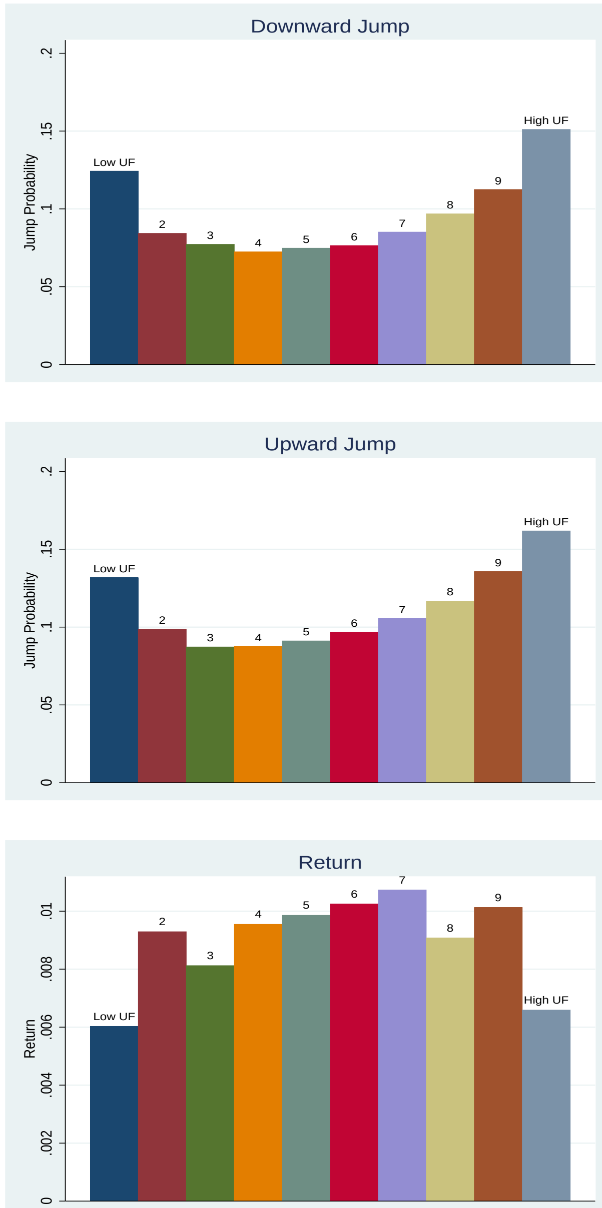

Figure 2: Portfolio Sorts by the Upward Jump Factor

This figure plots the average monthly probabilities of downward and upward jumps as well as the average monthly returns of decile portfolios of stocks sorted by the out-of-sample upward jump factor estimated based on an upward jump threshold of 15%. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample upward jump factor available as of the beginning of each month.

Table 1: Summary Statistics of Firm Characteristics

This table reports summary statistics of size, book-to-market ratio, profitability, investment, and illiquidity for the firms included in our sample. Firm size is the year-end market capitalization for the fiscal year that preceded the month of interest. Book-to-market is the ratio of the book value of equity to market capitalization as of the end of the preceding fiscal year. Firm profitability is measured following Hou, Xue, and Zhang (2015) as income before extraordinary items for the calendar year preceding the month of interest divided by one-quarter-lagged book equity. Firm investment is measured following Hou, Xue, and Zhang (2015) as the annual change in total assets for the calendar year preceding the month of interest scaled by one-year-lagged total assets. Amihud (2002) illiquidity is estimated as the average absolute daily return over daily trading volume during the calendar year that precedes the month of interest, scaled by the CRSP cross-sectional average of this illiquidity measure.

	Obs	Mean	Std.Dev	5%	10%	25%	50%	75%	90%	95%
Size	6,523	3.8909	15.0551	0.1021	0.1576	0.3036	0.7565	2.2964	6.6020	14.2939
Book-to-Market	6,523	0.5749	0.7149	0.0695	0.1478	0.2902	0.5043	0.7824	1.1041	1.3655
Profitability	6,523	0.0067	1.8210	-0.2438	-0.1233	-0.0181	0.0172	0.0337	0.0589	0.0975
Investment	6,523	0.2504	0.6862	-0.0891	-0.0204	0.0488	0.1313	0.2673	0.5235	0.8690
Illiquidity	6,523	0.0158	0.1033	0.0001	0.0001	0.0005	0.0020	0.0072	0.0201	0.0390

Table 2: Portfolio Sorts by the Downward Jump Factor

This table reports the average monthly probabilities of downward and upward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on downward jump thresholds of −10% (Panel A), −15% (Panel B), and −20% (Panel C). The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
			Panel A: Downward Jump Threshold of -10%								
DJ Prob	0.1810	0.1424	0.1341	0.1311	0.1345	0.1391	0.1527	0.1692	0.1944	0.2485	-0.0676***
											(0.0050)
UJ Prob	0.2134	0.1756	0.1648	0.1656	0.1654	0.1741	0.1823	0.1953	0.2114	0.2290	-0.0155***
											(0.0048)
Return	0.0130	0.0107	0.0097	0.0099	0.0098	0.0103	0.0097	0.0094	0.0078	-0.0006	0.0136***
											(0.0021)
Alpha	0.0042***	0.0011	-0.0003	-0.0006	-0.0004	0.0005	0.0005	0.0007	0.0000	-0.0073***	0.0115***
	(0.0014)	(0.0010)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0011)	(0.0014)	(0.0018)	(0.0022)
			Panel B: Downward Jump Threshold of -15%								
DJ Prob	0.1100	0.0771	0.0696	0.0690	0.0730	0.0778	0.0873	0.0991	0.1221	0.1700	-0.0601***
											(0.0050)
UJ Prob	0.1362	0.0985	0.0881	0.0862	0.0895	0.0976	0.1054	0.1173	0.1352	0.1589	-0.0227***
											(0.0044)
Return	0.0139	0.0113	0.0107	0.0099	0.0093	0.0110	0.0094	0.0092	0.0064	-0.0014	0.0153***
											(0.0020)
Alpha	0.0047***	0.0015	0.0004	-0.0005	-0.0007	0.0013	0.0004	0.0007	-0.0012	-0.0082***	0.0129***
	(0.0014)	(0.0009)	(0.0008)	(0.0009)	(0.0007)	(0.0009)	(0.0009)	(0.0013)	(0.0013)	(0.0017)	(0.0021)
			Panel C: Downward Jump Threshold of -20%								
DJ Prob	0.0687	0.0426	0.0394	0.0383	0.0399	0.0440	0.0496	0.0614	0.0776	0.1155	-0.0468***
											(0.0054)
UJ Prob	0.0932	0.0589	0.0510	0.0487	0.0497	0.0575	0.0631	0.0738	0.0878	0.1139	-0.0208***
											(0.0037)
Return	0.0140	0.0120	0.0108	0.0095	0.0092	0.0107	0.0104	0.0080	0.0064	-0.0014	0.0154***
											(0.0019)
Alpha	0.0044***	0.0029**	0.0003	-0.0010	-0.0008	0.0011	0.0011	-0.0003	-0.0015	-0.0076***	0.0119***
	(0.0012)	(0.0013)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0013)	(0.0016)	(0.0020)

Table 3: Portfolio Sorts by the Upward Jump Factor

This table reports the average monthly probabilities of downward and upward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample upward jump factor estimated based on upward jump thresholds of 10% (Panel A), 15% (Panel B), and 20% (Panel C). The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample upward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: Upward Jump Threshold of 10%						
DJ Prob	0.2038	0.1565	0.1428	0.1358	0.1378	0.1389	0.1501	0.1601	0.1793	0.2218	0.0180***
											(0.0060)
UJ Prob	0.2056	0.1774	0.1671	0.1653	0.1687	0.1773	0.1826	0.1945	0.2077	0.2307	0.0252***
											(0.0050)
Return	0.0052	0.0086	0.0088	0.0092	0.0096	0.0113	0.0092	0.0106	0.0101	0.0069	0.0018
											(0.0024)
Alpha	-0.0028*	0.0003	0.0001	-0.0002	-0.0009	0.0010	-0.0010	0.0009	0.0018	-0.0008	0.0019
	(0.0016)	(0.0014)	(0.0013)	(0.0009)	(0.0009)	(0.0008)	(0.0011)	(0.0011)	(0.0014)	(0.0016)	(0.0025)
					Panel B: Upward Jump Threshold of 15%						
DJ Prob	0.1243	0.0843	0.0773	0.0724	0.0748	0.0764	0.0852	0.0968	0.1125	0.1511	0.0268***
											(0.0049)
UJ Prob	0.1317	0.0988	0.0872	0.0874	0.0912	0.0966	0.1055	0.1168	0.1357	0.1618	0.0300***
											(0.0048)
Return	0.0060	0.0093	0.0081	0.0095	0.0099	0.0103	0.0107	0.0091	0.0101	0.0066	0.0006
											(0.0025)
Alpha	-0.0020	0.0004	-0.0016	-0.0002	-0.0002	0.0003	0.0010	-0.0003	0.0018	-0.0006	0.0015
	(0.0014)	(0.0009)	(0.0010)	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0010)	(0.0015)	(0.0017)	(0.0024)
					Panel C: Upward Jump Threshold of 20%						
DJ Prob	0.0767	0.0482	0.0427	0.0415	0.0398	0.0440	0.0510	0.0582	0.0715	0.1034	0.0268***
											(0.0041)
UJ Prob	0.0870	0.0598	0.0503	0.0510	0.0513	0.0564	0.0637	0.0727	0.0899	0.1156	0.0287***
											(0.0042)
Return	0.0065	0.0092	0.0089	0.0093	0.0099	0.0107	0.0099	0.0092	0.0104	0.0057	-0.0008
											(0.0024)
Alpha	-0.0018	-0.0001	-0.0010	-0.0010	-0.0005	0.0009	0.0007	0.0000	0.0022	-0.0009	0.0009
	(0.0013)	(0.0009)	(0.0011)	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0010)	(0.0016)	(0.0017)	(0.0023)

Table 4: Portfolio Sorts by the Downward Jump Factor Estimated Based on Call or Put

This table reports the average monthly probabilities of downward and upward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15% using implied volatilities of call options (Panel A) and put options (Panel B). The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: Call Options						
DJ Prob	0.1041	0.0820	0.0740	0.0720	0.0751	0.0799	0.0914	0.1033	0.1199	0.1534	-0.0494***
											(0.0064)
UJ Prob	0.1233	0.0919	0.0856	0.0838	0.0914	0.1000	0.1107	0.1235	0.1388	0.1637	-0.0405***
											(0.0047)
Return	0.0093	0.0080	0.0090	0.0081	0.0095	0.0100	0.0108	0.0094	0.0091	0.0063	0.0030
											(0.0022)
Alpha	-0.0004	-0.0006	-0.0012	-0.0023***	-0.0003	0.0002	0.0014	0.0004	0.0017	-0.0004	0.0001
	(0.0012)	(0.0014)	(0.0009)	(0.0008)	(0.0010)	(0.0009)	(0.0009)	(0.0011)	(0.0014)	(0.0017)	(0.0021)
					Panel B: Put Options						
DJ Prob	0.1074	0.0808	0.0742	0.0716	0.0743	0.0772	0.0885	0.1014	0.1197	0.1600	-0.0527***
											(0.0048)
UJ Prob	0.1269	0.0969	0.0915	0.0891	0.0885	0.0979	0.1076	0.1181	0.1370	0.1592	-0.0323***
											(0.0040)
Return	0.0108	0.0101	0.0109	0.0102	0.0087	0.0110	0.0090	0.0085	0.0086	0.0021	0.0087***
											(0.0019)
Alpha	0.0018	0.0020	0.0010	-0.0000	-0.0017**	0.0013	-0.0007	-0.0002	0.0002	-0.0050***	0.0068***
	(0.0012)	(0.0017)	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0014)	(0.0018)	(0.0019)

Table 5: Portfolio Sorts by the Downward Jump Factor Estimated Based on Short or Long Maturity

This table reports the average monthly probabilities of downward and upward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15% using implied volatilities with 30 days to maturity (Panel A) and more than 30 days to maturity (Panel B). The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: 30 Days to Maturity						
DJ Prob	0.1080	0.0955	0.0871	0.0832	0.0766	0.0765	0.0833	0.0920	0.1097	0.1433	-0.0353***
											(0.0047)
UJ Prob	0.1370	0.1179	0.1047	0.0955	0.0949	0.0936	0.0993	0.1064	0.1222	0.1412	-0.0041
											(0.0037)
Return	0.0130	0.0115	0.0100	0.0085	0.0102	0.0096	0.0088	0.0085	0.0077	0.0018	0.0112***
											(0.0022)
Alpha	0.0042***	0.0021**	0.0004	-0.0012	-0.0001	-0.0005	-0.0007	-0.0000	-0.0002	-0.0054**	0.0096***
	(0.0013)	(0.0010)	(0.0007)	(0.0009)	(0.0009)	(0.0007)	(0.0009)	(0.0012)	(0.0013)	(0.0023)	(0.0028)
					Panel B: More than 30 Days to Maturity						
DJ Prob	0.1095	0.0754	0.0703	0.0684	0.0725	0.0759	0.0875	0.0994	0.1240	0.1722	-0.0626***
											(0.0051)
UJ Prob	0.1363	0.0985	0.0864	0.0869	0.0875	0.0972	0.1060	0.1173	0.1365	0.1601	-0.0238***
											(0.0045)
Return	0.0139	0.0118	0.0103	0.0103	0.0095	0.0106	0.0101	0.0090	0.0063	-0.0019	0.0157***
											(0.0020)
Alpha	0.0047***	0.0018**	-0.0000	0.0002	-0.0006	0.0010	0.0012	0.0005	-0.0015	-0.0086***	0.0133***
	(0.0013)	(0.0009)	(0.0008)	(0.0007)	(0.0008)	(0.0009)	(0.0011)	(0.0011)	(0.0012)	(0.0017)	(0.0021)

Table 6: Correlation Between the Downward Jump Factor and Firm/Stock Characteristics

This table reports the pairwise correlation coefficients between the downward jump factor (DJF) and variables capturing firm and stock characteristics. These characteristics include the book-to-market (bm), cash holdings ($cash$), change in 6-month momentum (Δmom), change in number of analysts ($\Delta nanalyst$), earnings announcement return (ear), one-month momentum ($mom1m$), number of earnings increases ($nincr$), R&D to market capitalization ($rdmve$), return volatility ($retvol$), share turnover ($turn$), and volatility of share turnover ($turnvol$). The sample period is from January 1996 to December 2017. All variables are standardized to have zero mean and unit variance in each month.

	DJF	bm	$cash$	Δmom	$\Delta nanalyst$	ear	$mom1m$	$nincr$	$rdmve$	$retvol$	$turn$	$turnvol$
DJF	1											
bm	-0.0063	1										
$cash$	0.0618	-0.2421	1									
Δmom	0.0027	0.0467	-0.0207	1								
$\Delta nanalyst$	-0.0068	-0.0390	0.0231	-0.0168	1							
ear	-0.0164	0.0104	-0.0125	0.1409	0.0162	1						
$mom1m$	-0.0134	0.0073	-0.0065	0.2586	0.0014	0.0045	1					
$nincr$	-0.0129	-0.0475	0.0071	-0.0399	0.0183	0.1029	0.0055	1				
$rdmve$	0.0462	0.0969	0.3453	0.0384	-0.0151	-0.0074	0.0195	-0.0098	1			
$retvol$	0.1462	0.0044	0.3077	-0.0326	0.0046	-0.0300	0.0256	-0.0165	0.2537	1		
$turn$	0.1363	-0.0910	0.2155	-0.0545	0.0255	0.0049	-0.0166	0.0420	0.0689	0.3864	1	
$turnvol$	0.1186	-0.0646	0.1963	-0.0282	0.0121	0.0026	-0.0026	0.0215	0.0912	0.5632	0.6786	1

Table 7: Correlation Between the Downward Jump Factor and Option-Related Variables

This table reports the pairwise correlation coefficients between the downward jump factor (DJF) and other option-related characteristics. These characteristics include the implied volatility slope (ivs), volatility spread (vsp), call and put implied volatility innovations (Δciv and Δpiv), option to stock volume ratio ($osvolume$), call to put volume ratio ($cpvolume$), and call to put open interest ratio ($cpoi$). The sample period is from January 1996 to December 2017. All variables are standardized to have zero mean and unit variance in each month.

	DJF	ivs	vsp	Δciv	Δpiv	$osvolume$	$cpvolume$	$cpoi$
DJF	1							
ivs	-0.3237	1						
vsp	-0.0825	-0.0512	1					
Δciv	0.0172	0.2823	-0.2364	1				
Δpiv	0.2556	-0.1242	-0.2318	0.4847	1			
$osvolume$	0.0979	0.0011	0.0135	-0.0022	-0.0004	1		
$cpvolume$	-0.0041	-0.0050	-0.0356	-0.0036	-0.0040	-0.0197	1	
$cpoi$	-0.0001	0.0004	-0.0338	0.0027	0.0029	-0.0476	0.1853	1

Table 8: The Downward Jump Factor and Future Stock Return

This table reports the average slope coefficients from monthly cross-sectional regressions of the stock return on the downward jump factor (DJF) estimated from the previous month, controlling for lagged values of firm, stock, and option characteristics. These characteristics include the book-to-market (bm), cash holdings ($cash$), change in 6-month momentum (Δmom), change in number of analysts ($\Delta nanalyst$), earnings announcement return (ear), one-month momentum ($mom1m$), number of earnings increases ($nincr$), R&D to market capitalization ($rdmve$), return volatility ($retvol$), share turnover ($turn$), volatility of share turnover ($turnvol$), implied volatility slope (ivs), volatility spread (vsp), call and put implied volatility innovations (Δciv and Δpiv), option to stock volume ratio ($osvolume$), call to put volume ratio ($cpvolume$), and call to put open interest ratio ($cpoi$). The sample period is from January 1996 to December 2017. All independent variables are standardized to have zero mean and unit variance in each month. Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Dependent Variable: Future Stock Return				
DJF	-0.0044***	-0.0038***	-0.0049***	-0.0043***
	(0.0006)	(0.0006)	(0.0008)	(0.0007)
bm		0.0011		0.0005
		(0.0009)		(0.0008)
$cash$		0.0003		0.0002
		(0.0011)		(0.0011)
Δmom		0.0005		0.0004
		(0.0007)		(0.0007)
$\Delta nanalyst$		-0.0004		-0.0004
		(0.0003)		(0.0003)
ear		0.0010**		0.0010**
		(0.0004)		(0.0004)
$mom1m$		-0.0018*		-0.0020**
		(0.0010)		(0.0010)
$nincr$		0.0004		0.0005
		(0.0003)		(0.0003)
$rdmve$		0.0034**		0.0030*
		(0.0015)		(0.0015)
$retvol$		-0.0021		-0.0017
		(0.0022)		(0.0023)
$turn$		-0.0003		0.0004
		(0.0008)		(0.0008)
$turnvol$		-0.0003		-0.0004
		(0.0007)		(0.0007)
ivs			0.0008	0.0016***
			(0.0005)	(0.0005)
vsp			-0.0008	-0.0013**
			(0.0006)	(0.0005)
Δciv			0.0011*	0.0009
			(0.0006)	(0.0007)
Δpiv			0.0002	0.0007
			(0.0005)	(0.0006)
$osvolume$			-0.0012**	-0.0012**
			(0.0006)	(0.0005)
$cpvolume$			0.0007***	0.0011**
			(0.0003)	(0.0005)
$cpoi$			-0.0002	-0.0003
			(0.0004)	(0.0008)
Cons	0.0090**	0.0122***	0.0089**	0.0116**
	(0.0039)	(0.0046)	(0.0039)	(0.0046)

Table 9: The Downward Jump Factor, Short Interest Ratio, and Future Stock Return

This table reports the average slope coefficients from (1) monthly cross-sectional regressions of the stock return on the out-of-sample downward jump factor (DJF) estimated from the previous month, the lagged value of the higher-than-median short interest ratio dummy ($shortintH$), and their interaction, and (2) monthly cross-sectional regressions of the stock return on the out-of-sample downward jump factor (DJF) estimated from the previous month, the lagged value of the short interest ratio ($shortint$), and their interaction. The sample period is from July 2003 to December 2017. The jump factors and the short interest ratio are standardized to have zero mean and unit variance in each month. Newey-West standard errors with four lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Dependent Variable: Future Stock Return		
DJF	-0.0024***	-0.0037***
	(0.0006)	(0.0006)
$shortintH$	-0.0033***	
	(0.0010)	
$DJF \times shortintH$	-0.0030***	
	(0.0008)	
$shortint$		-0.0017***
		(0.0006)
$DJF \times shortint$		-0.0012***
		(0.0004)
Cons	0.0113**	0.0096**
	(0.0045)	(0.0047)

Table 10: The Downward Jump Factor, Institutional Holding, and Future Stock Return

This table reports the average slope coefficients from (1) monthly cross-sectional regressions of the stock return on the out-of-sample downward jump factor (DJF) estimated from the previous month, the lagged value of the lower-than-median institutional holding dummy ($instholdL$), and their interaction, and (2) monthly cross-sectional regressions of the stock return on the out-of-sample downward jump factor (DJF) estimated from the previous month, the lagged value of the institutional holding ($insthold$), and their interaction. The sample period is from January 1996 to December 2017. The jump factors and the institutional holding are standardized to have zero mean and unit variance in each month. Newey-West standard errors with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Dependent Variable: Future Stock Return		
DJF	-0.0027***	-0.0032***
	(0.0009)	(0.0007)
$instholdL$	-0.0013	
	(0.0011)	
$DJF \times instholdL$	-0.0016**	
	(0.0008)	
$insthold$		0.0011
		(0.0007)
$DJF \times insthold$		0.0009**
		(0.0004)
Cons	0.0108***	0.0102***
	(0.0036)	(0.0038)

Table 11: The Downward Jump Factor, Regulation SHO, and Future Stock Return

This table reports the slope coefficients from regressing the stock return on the out-of-sample downward jump factor (DJF) estimated from the previous month, the pilot stock dummy ($PilotStock$), the Regulation SHO month dummy ($SHOMonth$), and their interaction terms, controlling for the time-fixed effect. The sample period is from January 1996 to June 2007. The jump factors are standardized to have zero mean and unit variance in each month. Standard errors clustered at the stock level are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Dependent Variable: Future Stock Return	
DJF	-0.0021***
	(0.0006)
$PilotStock$	0.0001
	(0.0006)
$DJF \times PilotStock$	-0.0012
	(0.0011)
$DJF \times SHOMonth$	-0.0019
	(0.0014)
$PilotStock \times SHOMonth$	0.0008
	(0.0014)
$DJF \times PilotStock \times SHOMonth$	0.0048**
	(0.0020)
Cons	0.0125***
	(0.0003)
Time-Fixed Effect	Yes

Table 12: Portfolio Sorts by the Downward Jump Factor for Subperiods

This table reports the average monthly probabilities of downward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15% during different subperiods. The full sample period is from January 1996 to December 2017. Panels A and B include months with lower- and higher-than-median market returns. Panels C and D correspond to months with lower- and higher-than-median market volatilities. Panels E and F include expansion and recession months, respectively, according to the recession indicator from the website of the Federal Reserve Bank of St. Louis. Panels G and H divide the full sample according to the IV slope of S&P 500 options as a proxy of market sentiment. Panels I and J randomly divide the sample into two subperiods. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Robust standard errors are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: Low Market Return						
DJ Prob	0.1627	0.1183	0.1088	0.1084	0.1124	0.1219	0.1350	0.1514	0.1845	0.2501	-0.0874***
											(0.0067)
Return	-0.0317	-0.0284	-0.0274	-0.0282	-0.0288	-0.0299	-0.0329	-0.0359	-0.0437	-0.0596	0.0279***
											(0.0031)
Alpha	0.0041**	0.0013	0.0015	-0.0001	-0.0005	0.0000	0.0003	0.0001	-0.0000	-0.0087***	0.0128***
	(0.0020)	(0.0013)	(0.0012)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0013)	(0.0018)	(0.0025)	(0.0029)
					Panel B: High Market Return						
DJ Prob	0.0572	0.0359	0.0306	0.0296	0.0336	0.0337	0.0397	0.0468	0.0598	0.0899	-0.0328***
											(0.0030)
Return	0.0594	0.0509	0.0488	0.0479	0.0474	0.0519	0.0516	0.0544	0.0566	0.0568	0.0026
											(0.0037)
Alpha	-0.0017	0.0038	0.0031	0.0018	0.0002	0.0071***	0.0057*	0.0007	-0.0031	-0.0079	0.0062
	(0.0039)	(0.0035)	(0.0024)	(0.0025)	(0.0023)	(0.0026)	(0.0031)	(0.0035)	(0.0039)	(0.0055)	(0.0068)

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel C: Low Market Volatility						
DJ Prob	0.0798	0.0511	0.0449	0.0426	0.0449	0.0487	0.0541	0.0648	0.0826	0.1274	-0.0476***
											(0.0040)
Return	0.0107	0.0103	0.0105	0.0093	0.0088	0.0092	0.0086	0.0069	0.0052	-0.0032	0.0139***
											(0.0017)
Alpha	0.0031**	0.0014	0.0013	-0.0001	-0.0019**	-0.0008	-0.0008	-0.0022	-0.0027**	-0.0104***	0.0135***
	(0.0014)	(0.0009)	(0.0010)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0011)	(0.0012)	(0.0018)	(0.0019)
					Panel D: High Market Volatility						
DJ Prob	0.1401	0.1032	0.0942	0.0953	0.1011	0.1069	0.1205	0.1334	0.1617	0.2127	-0.0726***
											(0.0069)
Return	0.0170	0.0122	0.0110	0.0105	0.0098	0.0128	0.0101	0.0115	0.0076	0.0004	0.0166***
											(0.0048)
Alpha	0.0066**	0.0020	-0.0002	-0.0003	-0.0002	0.0028**	0.0012	0.0024	0.0003	-0.0061*	0.0127***
	(0.0026)	(0.0018)	(0.0014)	(0.0015)	(0.0015)	(0.0014)	(0.0016)	(0.0019)	(0.0021)	(0.0031)	(0.0041)
					Panel E: Expansion						
DJ Prob	0.1134	0.0808	0.0725	0.0724	0.0772	0.0817	0.0912	0.1041	0.1268	0.1785	-0.0651***
											(0.0047)
Return	0.0111	0.0095	0.0088	0.0080	0.0073	0.0094	0.0074	0.0068	0.0042	-0.0050	0.0161***
											(0.0030)
Alpha	0.0047***	0.0017	0.0005	-0.0005	-0.0009	0.0018*	0.0006	0.0008	-0.0005	-0.0082***	0.0129***
	(0.0016)	(0.0012)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0011)	(0.0013)	(0.0015)	(0.0020)	(0.0025)
					Panel F: Recession						
DJ Prob	0.0932	0.0592	0.0560	0.0524	0.0525	0.0592	0.0685	0.0751	0.0995	0.1293	-0.0362***
											(0.0055)
Return	0.0270	0.0202	0.0199	0.0191	0.0188	0.0184	0.0193	0.0207	0.0172	0.0157	0.0112***
											(0.0031)
Alpha	0.0038	0.0008	0.0011	-0.0008	-0.0001	0.0001	0.0004	0.0003	-0.0034	-0.0049*	0.0087**
	(0.0028)	(0.0013)	(0.0022)	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0016)	(0.0022)	(0.0026)	(0.0033)

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel G: Pessimistic						
DJ Prob	0.1284	0.0925	0.0851	0.0856	0.0890	0.0937	0.1050	0.1182	0.1390	0.1944	-0.0660***
											(0.0060)
Return	0.0158	0.0125	0.0098	0.0086	0.0088	0.0113	0.0096	0.0095	0.0090	0.0008	0.0150***
											(0.0040)
Alpha	0.0063***	0.0035**	0.0000	-0.0010	-0.0008	0.0014	0.0005	0.0001	-0.0007	-0.0091***	0.0154***
	(0.0022)	(0.0015)	(0.0014)	(0.0013)	(0.0012)	(0.0012)	(0.0014)	(0.0015)	(0.0020)	(0.0028)	(0.0036)
					Panel H: Optimistic						
DJ Prob	0.0915	0.0618	0.0541	0.0524	0.0570	0.0620	0.0696	0.0800	0.1052	0.1457	-0.0542***
											(0.0056)
Return	0.0120	0.0100	0.0116	0.0112	0.0099	0.0106	0.0092	0.0089	0.0039	-0.0036	0.0155***
											(0.0031)
Alpha	0.0025	-0.0005	0.0009	0.0004	-0.0012	-0.0002	-0.0001	0.0006	-0.0027**	-0.0096***	0.0121***
	(0.0020)	(0.0013)	(0.0011)	(0.0011)	(0.0012)	(0.0010)	(0.0011)	(0.0013)	(0.0013)	(0.0019)	(0.0024)
					Panel I: Random Subperiods 1						
DJ Prob	0.1156	0.0809	0.0738	0.0732	0.0763	0.0804	0.0886	0.1007	0.1252	0.1704	-0.0548***
											(0.0050)
Return	0.0140	0.0113	0.0089	0.0091	0.0078	0.0105	0.0097	0.0102	0.0086	0.0031	0.0108***
											(0.0037)
Alpha	0.0050**	0.0030*	-0.0002	-0.0003	-0.0004	0.0016	0.0011	0.0006	0.0002	-0.0047**	0.0097***
	(0.0021)	(0.0015)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0014)	(0.0015)	(0.0018)	(0.0022)	(0.0029)
					Panel J: Random Subperiods 2						
DJ Prob	0.1048	0.0738	0.0657	0.0650	0.0701	0.0754	0.0861	0.0976	0.1193	0.1697	-0.0649***
											(0.0062)
Return	0.0137	0.0112	0.0124	0.0106	0.0106	0.0114	0.0091	0.0083	0.0045	-0.0055	0.0193***
											(0.0035)
Alpha	0.0034*	0.0005	0.0020	-0.0001	-0.0004	0.0010	-0.0004	0.0001	-0.0032*	-0.0123***	0.0157***
	(0.0018)	(0.0011)	(0.0013)	(0.0012)	(0.0012)	(0.0010)	(0.0010)	(0.0015)	(0.0018)	(0.0027)	(0.0032)

Table 13: Portfolio Sorts by the Downward Jump Factor for Big, Small, and Microcap Firms

This table reports the average monthly probabilities of downward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15% for big (Panel A), small (Panel B), and microcap (Panel C) firms. The sample period is from January 1996 to December 2017. We split our sample of stocks by the 50^{th} and 20^{th} percentile of the NYSE stock sizes. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Robust standard errors are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: Big Firms						
DJ Prob	0.1159	0.0782	0.0717	0.0703	0.0738	0.0782	0.0903	0.0999	0.1246	0.1660	0.0501***
											(0.0043)
Return	0.0119	0.0100	0.0096	0.0093	0.0098	0.0101	0.0088	0.0099	0.0067	0.0013	0.0106***
											(0.0025)
Alpha	0.0030**	0.0009	-0.0001	-0.0011	-0.0002	0.0007	-0.0002	0.0013	-0.0011	-0.0048***	0.0078***
	(0.0030)	(0.0012)	(0.0009)	(0.0010)	(0.0007)	(0.0008)	(0.0010)	(0.0011)	(0.0013)	(0.0017)	(0.0022)
					Panel B: Small Firms						
DJ Prob	0.1185	0.0870	0.0784	0.0743	0.0745	0.0752	0.0845	0.0972	0.1148	0.1646	-0.0461***
											(0.0040)
Return	0.0131	0.0100	0.0103	0.0082	0.0095	0.0108	0.0094	0.0082	0.0074	0.0002	0.0130***
											(0.0024)
Alpha	0.0045***	-0.0004	0.0010	-0.0017*	0.0000	0.0013	0.0007	0.0000	-0.0004	-0.0065***	0.0109***
	(0.0014)	(0.0011)	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0013)	(0.0019)	(0.0024)
					Panel C: Micro-Cap Firms						
DJ Prob	0.1263	0.0975	0.0857	0.0766	0.0762	0.0773	0.0783	0.0879	0.1079	0.1552	-0.0290***
											(0.0043)
Return	0.0108	0.0105	0.0099	0.0100	0.0094	0.0092	0.0094	0.0086	0.0075	0.0020	0.0088***
											(0.0025)
Alpha	0.0035**	0.0027**	0.0012	0.0008	-0.0001	-0.0005	-0.0007	-0.0006	-0.0020	-0.0060***	0.0095***
	(0.0017)	(0.0012)	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0012)	(0.0019)	(0.0027)

Table 14: Portfolio Double-Sorted by the Downward Jump Factor and Short-Sale Constraint Proxy

This table reports the average monthly probabilities of downward jumps, the average monthly returns, and the risk-adjusted alphas of double-sorted portfolios. The stocks are sorted by their institutional holding ratios (Panel A) or short interest ratios (Panel B) into five quintiles. Within each quintile, the stocks are further sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of -15%. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on information available as of the beginning of each month. The average return of a long short portfolio within each quintile is reported in the last row of each panel. Newey-West standard errors are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Panel A: Sorting by Institutional Holding Ratio and the DJF

		Institutional Holdings				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0132	0.0146	0.0141	0.0136	0.0128
	Q2	0.0103	0.0114	0.0102	0.0121	0.0104
	Q3	0.0099	0.0107	0.0112	0.0106	0.0110
	Q4	0.0052	0.0113	0.0116	0.0113	0.0097
	High	-0.0031	0.0064	0.0087	0.0097	0.0080
	Low-High	0.0163***	0.0082***	0.0055**	0.0039**	0.0049**
		(0.0024)	(0.0022)	(0.0023)	(0.0020)	(0.0020)

Panel B: Sorting by Short Interest Ratio and the DJF

		Short Interest				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0150	0.0132	0.0143	0.0116	0.0107
	Q2	0.0130	0.0104	0.0109	0.0098	0.0077
	Q3	0.0118	0.0103	0.0098	0.0115	0.0083
	Q4	0.0123	0.0106	0.0092	0.0093	0.0049
	High	0.0089	0.0095	0.0068	0.0045	-0.0038
	Low-High	0.0061***	0.0037***	0.0074***	0.0070***	0.0145***
		(0.0017)	(0.0014)	(0.0020)	(0.0020)	(0.0030)

Table 15: Portfolio Sorts by the Downward Idiosyncratic Jump Factor

This table reports the average monthly probabilities of downward jumps, the average monthly returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward idiosyncratic jump factor estimated based on a downward idiosyncratic jump threshold of -15%. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Robust standard errors are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
DJ Prob	0.1112	0.0783	0.0712	0.0680	0.0733	0.0784	0.0845	0.1008	0.1205	0.1688	-0.0576***
											(0.0046)
Return	0.0127	0.0114	0.0100	0.0110	0.0097	0.0099	0.0104	0.0075	0.0070	0.0003	0.0124***
											(0.0021)
Alpha	0.0037***	0.0020	-0.0004	0.0005	-0.0004	-0.0001	0.0013	-0.0009	-0.0009	-0.0064***	0.0100***
	(0.0013)	(0.0015)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0012)	(0.0013)	(0.0017)	(0.0020)

Table 16: Portfolio Sorts by the Downward Jump Factor for Longer Investment Horizons

This table reports the average probabilities of downward jumps, the average returns, and the risk-adjusted alphas of decile portfolios of stocks sorted by the out-of-sample downward jump factor estimated based on a downward jump threshold of −15% over the next three (Panel A), Six (Panel B), Nine (Panel C), and 12 (Panel D) months. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the out-of-sample downward jump factor available as of the beginning of each month, but are held for the next few months with overlapping investment horizons. The alphas are estimated with respect to the Fama and French (2015) five factors, the momentum factor of Carhart (1997), and the liquidity factor of Pástor and Stambaugh (2003). Robust standard errors are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel A: Three Months						
DJ Prob	0.2094	0.1599	0.1501	0.1494	0.1532	0.1628	0.1730	0.1942	0.2214	0.2829	-0.0735
											(0.0072)***
Return	0.0346	0.0336	0.0314	0.0305	0.0292	0.0296	0.0297	0.0260	0.0217	0.0015	0.0331
											(0.0044)***
Alpha	0.0126	0.0077	0.0054	0.0030	0.0037	0.0044	0.0032	0.0019	-0.0016	-0.0168	0.0294
	(0.0036)***	(0.0024)***	(0.0021)**	(0.0021)	(0.0021)*	(0.0031)	(0.0026)	(0.0028)	(0.0026)	(0.0044)***	(0.0045)***
					Panel B: Six Months						
DJ Prob	0.2603	0.2058	0.1947	0.1946	0.1991	0.2103	0.2225	0.2436	0.2716	0.3399	-0.0796
											(0.0103)***
Return	0.0672	0.0655	0.0619	0.0619	0.0570	0.0579	0.0570	0.0524	0.0456	0.0128	0.0544
											(0.0089)***
Alpha	0.0223	0.0161	0.0127	0.0129	0.0111	0.0124	0.0094	0.0071	0.0013	-0.0245	0.0468
	(0.0089)**	(0.0055)***	(0.0051)**	(0.0061)**	(0.0052)**	(0.0057)**	(0.0055)*	(0.0055)	(0.0054)	(0.0095)**	(0.0081)***

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel C: Nine Months						
DJ Prob	0.2814	0.2302	0.2192	0.2165	0.2238	0.2334	0.2447	0.2671	0.2951	0.3596	-0.0782
											(0.0119)***
Return	0.1070	0.0990	0.0921	0.0941	0.0869	0.0862	0.0865	0.0802	0.0695	0.0353	0.0717
											(0.0124)***
Alpha	0.0290	0.0234	0.0161	0.0152	0.0100	0.0120	0.0101	0.0081	0.0043	-0.0311	0.0601
	(0.0112)**	(0.0069)***	(0.0075)**	(0.0089)*	(0.0070)	(0.0077)	(0.0080)	(0.0082)	(0.0093)	(0.0128)**	(0.0115)***
					Panel D: 12 Months						
DJ Prob	0.2910	0.2420	0.2311	0.2304	0.2357	0.2464	0.2571	0.2787	0.3076	0.3671	-0.0762
											(0.0138)***
Return	0.1444	0.1349	0.1238	0.1281	0.1177	0.1161	0.1168	0.1120	0.1009	0.0653	0.0791
											(0.0161)***
Alpha	0.0297	0.0293	0.0203	0.0181	0.0134	0.0125	0.0119	0.0080	0.0019	-0.0284	0.0581
	(0.0190)	(0.0118)**	(0.0100)**	(0.0126)	(0.0096)	(0.0094)	(0.0113)	(0.0107)	(0.0153)	(0.0194)	(0.0166)***