The Information Content of The Implied Volatility Surface: How to More Efficiently Use Option Information to Predict Stock Returns?*

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Abstract

Applying the partial least squares (PLS) approach to the entire implied volatility (IV) surface, we show that option prices predict downward jumps, but not upward jumps, in the underlying stock prices. The long-short portfolio formed based on the estimated downward jump factor yields an annual return of 18.36% with a Sharpe ratio of 1.29. The predictability of the downward jump factor is very robust and much stronger than that of other IV-related predictors. Finally, we show that the predictability is consistent with the notion that informed investors trade options to profit from negative information to circumvent the equity short-sale constraint.

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 to make directional bets due to the embedded leverage and the absence of short-sale constraint in the options markets. Therefore, information is likely incorporated into the options markets first. The current literature has found that option prices can predict underlying future stock movements. However, there are several potential issues with the current research in the literature.

First, given the potential high cost of option premium, issue of expiration, and embedded leverage, betting on stock price movement by 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. As a result, option prices may only have information about relatively large directional price movements of the underlying stocks, which we call "jumps" hereafter.

Second, there are hundreds of options traded at the same time for each stock, differing by maturity and moneyness. However, the current literature often makes somewhat ad hoc choice of the options, for example, using at-the-money call and out-of-the-money put options with 30 days to maturity (Xing, Zhang, and Zhao, 2010). The vast majority of the options are simply discarded, which likely results in loss of information.

In this paper, we ask the question how most efficiently extract information from the option prices to help predict the underlying stock prices. To this end, we employ the partial least squares (PLS) approach pioneered by Wold (1966, 1975) and extended by Kelly and Pruitt (2013, 2015), Huang, Jiang, Tu, and Zhou (2015), and Light, Maslov and Rytchkov (2017) to extract the latent jump information from option prices. 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 call and put options which differ by the strike price (moneyness) and maturity, each option has an implied volatility (IV), and thus all the IVs constitute the IV surface. We first propose to use the entire IV surface to extract the information about jumps in the underlying stock prices, which we call the latent jump factor. We then use it to forecast future stock returns, and we find very strong results.

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 IV positions, each of which can be viewed as a different variable. A similar approach is the principal component analysis (PCA). However, the key difference lies in what information is extracted. PCA extracts the common variations of IVs at different positions based only on their covariance structure, and therefore the information extracted may not be relevant for forecasting jumps. Indeed, results not reported in the paper suggest that there is no out-of-sample predicability using the PCA approach. On the other hand, by projecting the IVs to the observed return jumps, the PLS approach extracts information that is most relevant to the prediction of jumps in stock returns. From the machine learning perspective, PCA is an unsupervised learning approach whereas PLS is a supervised learning approach. In addition, the PLS approach enables us to consider downward and upward jumps separately and obtain an estimated downward jump factor and an upward jump factor.

Empirically, we extract out-of-sample jump factors and test whether they can predict the future realized jump probabilities and future stock returns. We define downward (upward) jumps as returns below (above) a certain threshold, and we use −15% as the main threshold, but results are similar if we use −10% or −20%. When we use the estimated downward jump factor to sort stocks into decile portfolios, stocks in the top (bottom) decile have an average downward jump probability of 17% (11%) in the subsequent month, with a statistically significant spread of 6%. In addition, the downward jump factor is negatively related to future monthly stock returns with the bottom and top deciles earning 1.39% and −0.14%, respectively. This leads to a long-short trading strategy with an annualized return of 18.36% and a Sharpe ratio of 1.29. The risk-adjusted alpha accounting for the Fama-French five factors, momentum, and illiquidity is economically large and strongly significant. In contrast, an estimated jump factor targeting upward jumps cannot significantly predict future returns. These results are consistent with the notion that informed traders with big negative news would choose to trade on the options markets to take advantage of the embedded leverage and to avoid the costly short selling of stocks.

We further explore the source of the predictive information along two dimensions. The first is whether the information content is affected by using put versus call as well as the moneyness of options. We find that the information is largely concentrated in the out-of-the-money (OTM) and in-the-money (ATM) put options, suggesting that purchasing OTM/ATM put options is the dominant strategy to profit from negative information. However, the performance of using the OTM/ATM puts is much weaker than using the all the options, suggesting the much improved efficiency of utilizing information in the entire IV surface. The second is whether IVs with different time to maturity contain different information. While options with exactly one month to maturity do contain predictive information on returns for the next month, more or better information is contained in the options with longer maturities. This finding highlights the inefficiency of the common approaches in the literature that only focus on options with one-month maturity.

We further explore the economic channel behind the information content of option prices regarding future downward jumps. A possible explanation could be that informed investors trade options to circumvent the short-sale constraint in the equity market, which incorporates negative information into option prices. If this is the case, we would expect stronger predictability for stocks subject to tighter short-sale constraints. We conduct three tests to confirm this hypothesis. The first two tests use the short interest ratio and institutional ownership (following Berkman, Dimitrov, Jain, Koch, and Tice (2009)), respectively, as two proxies for the tightness of short-sale constraints in Fama-MacBeth style regressions. In the third test, we exploit the Pilot Program of Regulation SHO from 2005 to 2007 as a quasi-experiment to examine the effect of loosening the short-sale constraint on the predictive power of our estimated downward jump factor. All three tests show that the information content of our estimate is significantly stronger when the short-sale constraint is more binding.

Finally, we run horse race between the downward jump factor and other IV related variables documented in the literature that have predictive powers over stock returns.

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 describe the return 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 particularly related to the literature that not only estimates or forecasts jumps but also uses those jump estimates 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 IV 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 largely explain the size, value, and illiquidity anomalies. 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 to avoid loss of information. Previous studies such as Xing, Zhang, and Zhao (2010) and Yan (2011) only use a few IV positions and choose them in *ad hoc* ways. Second, we differentiate downward from upward jumps, whereas most previous studies do not make the distinction.[1] This allows us to better examine the economic channel behind the predictability.

On this note, our paper is also related to the literature that studies downside risk and tail risk. Several recent papers such as Bakshi, Kapadia, and Madan (2003), 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 provides an alternative measurement of 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. Section 3 discusses the data and main results. Section 4 explores the economic channel of the predictability by relating the predictive power of the downward jump factor 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.

[1] One exception is Kapadia and Zekhnini (2019) who separate jumps into positive and negative ones.

2.1. A Latent Factor Model

Consider N stocks indexed by $i = 1, 2, \ldots, N$ with traded options. Suppose that for each stock, we observe M different moneyness-maturity combinations for the option-implied volatility (IV), with $m = 1, 2, \ldots, M$. Let $q_{i,t}^D$ represent a latent factor dictating the likelihood of future downward jumps of stock i as of month t. We assume that in month t, the IV of each stock i at each moneyness-maturity combination m, $IV_{i,t,m}$, is linearly related to the latent downward jump factor through

$$IV_{i,t,m} = c_{t,m} + \pi_{t,m} q_{i,t}^D + e_{i,t,m}, \tag{1}$$

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

Two remarks are worth noting here. First, Eq. (1) 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, $e_{i,t,m}$. Second, for any specific moneyness-maturity combination m, the sensitivity parameter, $\pi_{t,m}$, 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 observed 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 only on the correlation structure among the predictors, 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 jumps in 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 at the end of month t, which encode the jump risk of each stock in month $t+1$.

2.2.1. First Stage

In the first stage, for each moneyness-maturity combination m, 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.,

$$IV_{i,t-1,m} = \gamma_{t-1,m} + \lambda_{t-1,m} 1^{D}_{i,t} + \theta_{i,t-1,m}, \tag{2}$$

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

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

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

Utilizing the assumption that the sensitivity parameter, $\pi_{t-1,m}$, is constant across stocks, we can estimate it using cross-sectional regressions. Here we choose the downward jump dummy in the following month, $1^D_{i,t}$, as a proxy the unobservable latent downward jump factor $q^D_{i,t-1}$. The choice of this proxy is natural, because 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, $\widehat{\lambda}_{t-1,m}$, can be viewed as an estimator of $\pi_{t-1,m}$. 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 $\widehat{\lambda}_{t-1,m}$ from the first stage, across all moneyness-maturity combinations, i.e.,

$$IV_{i,t,m} = \delta_{i,t} + DJF_{i,t} \widehat{\lambda}_{t-1,m} + \eta_{i,t,m}. \tag{3}$$

We run a total of N such regressions, one for each stock i. The use of $\widehat{\lambda}_{t-1,m}$ makes sure that all information required to perform these regressions, in particular the downward jump realizations in month t needed to estimate $\widehat{\lambda}_{t-1,m}$ in the first stage, is available as of month t. 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 the prediction of jumps in month

$t+1$.[2]

Again, the second stage can be understood in relation to the latent factor model in Eq. (1). We implicitly assume that $\pi_{t,m} = \pi_{t-1,m}$, and use $\widehat{\lambda}_{t-1,m}$ to proxy for $\pi_{t-1,m}$. Intuitively, this assumption states that the relation between the IVs and the latent downward jump factor is persistent from one month to the next. This assumption enables us to predict stock returns in month $t+1$ with information available at the end of month t.

3. Empirical Analysis

In this section, we estimate the downward and upward jump factors using the PLS approach for a large set of common stocks with traded options 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 maturities 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.

[2] Light, Maslov and Rytchkov (2017) use the rolling-window average of $\widehat{\lambda}$ as the regressor in the second stage regression (3). We repeat our empirical analysis using this approach in Section 5.6 for robustness check.

In addition, we also obtain monthly stock returns from CRSP.

Our sample includes all the stocks that have available IV surface data. Panel A of Table 1 reports the summary statistics of firm characteristics of the stocks in our sample. We have around 4700 stocks. As all the stocks under consideration have relatively liquid option trading, they are mostly 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] Panel B of Table 1 reports the summary statistics of the same firm characteristics for the entire CRSP sample for comparison. We can see that, as expected, our sample of stocks with liquid options are larger in size, lower in value, higher in profitability and investment, and more liquid.

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.

We estimate the PLS downward and upward jump factors at a monthly frequency for each stock out of sample based on different jump thresholds. Figure 1 presents the time-series of the cross-sectional average of the DJF based on a -15% downward jump threshold.

[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 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.

The average DJF is positive most of the time.[5] There are two clear spikes. The first one corresponds to the burst of the dot-com bubble in the early 2000s, and the second one is during the 2008 financial crisis. The biggest drop happens in September 2008, during which Lehman Brothers collapsed and asset prices were extremely volatile. Under normal economic conditions, the average DJF gradually rises before a crisis and drops to around zero following the crisis.

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 for stocks in different decile portfolios in the following month.

The results are displayed in Figure 2 (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 exhibits a much weaker relation with the DJF. The bottom and top deciles have similar upward jump probabilities of 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 ability to distinguish the direction of jumps is crucial, enabling us to use the information effectively for making directional bets. Accordingly, the average stock return has a clear inverse relation with the DJF, consistent with the fact that stocks in higher deciles

[5] Being a latent factor, the magnitude of DJF has no particular meaning.

are more likely to experience crashes and hence deliver lower realized returns. 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.[6] 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% 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).[7] This abnormal return comes from both the long and the short positions. Hence, we can identify stocks that are most likely to experience a downward jump by analyzing the one-month-lagged 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 3 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 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

[6]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.

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

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. Hereafter, we will focus on the performance of the DJF estimated with the jump threshold of -15%, and 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 from 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 put versus call as well as the moneyness of options used for our estimation. The second is whether the information content is affected by the time to maturity of the IVs. Below we address these two questions in turn.

3.3.1. Put/Call and Moneyness

An investor with information on a future downward jump of a stock can potentially make a profit by either writing a call or buying a put. In addition, s/he could also choose to trade options with different moneyness. These are different possible channels through which information on a future downward jump can get incorporated into current option prices. Which of these 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 divide the entire IV surface into four regions: out-of-the-money (OTM) and at-the-money (ATM) put, OTM and ATM call, in-the-money

(ITM) put, and ITM call. We re-estimate the DJF by using only IVs in each of these four regions separately and compare their predictive power.

Table 4 reports the findings. We start by estimating the DJF using IVs of OTM and ATM put options only. Our previous results continue to hold. The realized downward jump probability is higher for the top decile than for the bottom decile by 5.94%, whereas the realized upward jump probability is higher for the top decile than for the bottom decile by only 3.90%. 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 the 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 11.16% and an annualized Sharpe ratio of 0.88. The alpha of the strategy is also significantly positive at the 1% level. This indicates that OTM and ATM put option prices alone contain information for the prediction of downward jumps.

When we repeat the analysis using IVs in the other three regions, the results disappear. The key issue again is that the corresponding DJF cannot distinguish the likelihood of downward jumps from that of upward ones, as reflected in the similar differences in the subsequent realized probabilities of downward versus upward jumps between the bottom and top deciles. As a result, the relation between the DJF and the stock return is unclear. However, it is worth noting that these three regions of the IV surface are still useful in predicting stock returns as the performance of using only OTM and ATM put options is much weaker than using the entire surface.

Overall, our findings show that negative information regarding downward jumps of the underlying stocks is primarily reflected in prices of OTM and ATM put options. This suggests that buying OTM and ATM put options is a more effective channel than other option strategies for the incorporation of negative information into option prices. This is intuitive, as OTM and ATM options are in general more actively traded, and purchasing puts delivers greater profits in the case of large downward jumps compared to writing calls, which has limited upside.[8]

3.3.2. Time to Maturity

We have been primarily concerned with the prediction of jumps and returns over a monthly horizon. Given this, one would expect that prices of options with exactly one month to maturity should be the most relevant, and that options with longer maturity may not provide additional information. To see if this is the case, 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. Accordingly, 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%, 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% and an annualized Sharpe ratio

[8]We thank Felipe Aguerrevere for pointing this out.

of 1.33. These numbers are close to the baseline results obtained using IVs of all maturity levels.[9]

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 of American style, 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.[10]

3.4. Controlling for Other Characteristics

We have shown that the estimated DJF negatively predicts future stock returns. We now ask whether this relation could be explained by other variables 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.

[9] We also repeat the analysis with options that have maturities longer than one year. Significant results still hold.

[10] We also test the performance of the DJF based on IVs with 30 days to maturity and IVs with more than 30 days to maturity for calls and puts separately. Difference between the results relying on the two maturity groups is more significant for puts than for calls. This provides further supporting evidence for our argument, as deep-in-the-money puts are more likely to be exercised early than calls in general. The results are available upon request.

- 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. It is of particular interest to see if the DJF provides useful information beyond what is in these IV related variables as the DJF is estimated using the entire IV surface.

- Implied volatility slope/skewness (*ivs*): Xing, Zhang, and Zhao (2010) define *ivs* as the difference between the ATM call IV (delta of 0.5) and the OTM 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 ATM call IV (delta of 0.5) and ATM 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 ATM 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 ATM call IV (delta of 0.5) and the ATM 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. The literature has shown that such variables are related to stock returns (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 DJF and other characteristics in each month to have zero mean and unit variance to allow for easier interpretation.

We start by examining the correlations among different characteristics. Table 6 reports the pairwise correlation coefficients of our DJF 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 a correlation coefficient of 0.1462. This is intuitive, because the DJF is 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 the option-related variables. The correlations are generally stronger between the 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 returns 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.

Controlling for the firm and stock characteristics slightly reduces (in magnitude) the coefficient of DJF to -0.0038. On the other hand, controlling for the option characteristics actually increases (in magnitude) the DJF coefficient to -0.0049, in spite of the sizable correlations between these variables and the DJF. 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 fact, the opposite is true. Contrasting the regression coefficients on the control variables with and without DJF, respectively, shows that while adding DJF does not influence the relation between the firm/stock characteristics and future stock returns, DJF almost completely subsumes the effects of the IV-related option characteristics—the IV slope (ivs) and put IV innovation (Δpiv), which have the highest correlations with the DJF, completely lose their significance, and the significance of Δciv is also weakened from 5% to 10%. These results highlight the importance of using information available from all options, not just a small set of predetermined options.

It is also worth noting that the coefficients of the control variables are much smaller in magnitude than that of the DJF. For example, R&D to market capitalization ($rdmve$) has a coefficient of 0.0034, the largest among all control variables, but it is still smaller than that of the DJF. This suggests that the DJF not only provides information on future stock returns independent of that reflected in other characteristics, its predictive power is also stronger than any of these variables, and in particular those IV-related variables.

4. Economic Channel

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 sellers 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 constraints. Below we test this hypothesis in three different ways. First, we use the short interest ratio as a proxy for the tightness of the short-sale constraint. Second, we use institutional ownership to measure how binding the short-sale constraint is. Finally, we exploit the Pilot Program of Regulation SHO from 2005 to 2007 as a quasi-experiment to examine the effect of loosening the short-sale constraint on the predictive power of our estimated DJF.

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*.[11] Intuitively, a higher short interest ratio implies fewer borrowable shares available, which imposes a constraint on investors' ability 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 a dummy variable that equals one if the short interest ratio for stock i in month t is higher than the median value for all stocks in that month. For each month t, we cross-sectionally regress the stock return on the lagged values of the DJF, the high short interest dummy, and their interaction, i.e.,

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

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

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 interests.

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 interests, a one-standard-deviation increase in the DJF predicts a 0.24% decrease in the monthly stock return. The coefficient on the high short interest dummy is also significantly negative, implying that on average stocks with higher short interests 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 interests, 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 interests. Equivalently, for stocks with high short interests, 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 (4) by replacing the dummy with the actual log short interest ratio, i.e.,

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

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/or higher short interests 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 interests.

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

4.2. Institutional Ownership

Following Berkman, Dimitrov, Jain, Koch, and Tice (2009), we use the institutional ownership as a second proxy for 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 higher institutional ownership generally have less binding short-sale constraints.[12] We define the institutional ownership, *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 $instholdL_{i,t}$ denote a dummy variable that equals one if the institutional ownership, $insthold_{i,t}$, for stock i in month t is lower than the median value 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 ownership dummy, and their interaction, i.e.,

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

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

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

stock return is stronger for stocks with tighter short-sale constraints as characterized by lower institutional ownership.

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 ownership, 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 ownership, 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 ownership. Equivalently, for stocks with low institutional ownership, 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 (6) by replacing the low institutional ownership dummy with the actual institutional ownership level, i.e.,

$$ret_{i,t} = b_{0,t} + b_{1,t}DJF_{i,t-1} + b_{2,t}insthold_{i,t-1} + b_{3,t}DJF_{i,t-1} \times insthold_{i,t-1} + \phi_{i,t}, \quad (7)$$

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 earn lower returns. Furthermore, the coefficient on the interaction term, $b_{3,t}$, is now significantly positive, confirming that the negative relation between the DJF and future stock returns is significantly stronger for firms with lower institutional ownership.

In sum, we have found that the DJF performs better in predicting future stock returns when institutional ownership 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 ownership, are potentially 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 constraints affect 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 the 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.[13] 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,

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

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:

$$\begin{aligned} ret_{i,t} &= b_0 + b_1 DJF_{i,t-1} + b_2 DJF_{i,t-1} \times PilotStock_i \\ &+ b_3 DJF_{i,t-1} \times SHOMonth_t + b_4 PilotStock_i \times SHOMonth_t \\ &+ b_5 DJF_{i,t-1} \times PilotStock_i \times SHOMonth_t + \eta_t + \delta_i + \phi_{i,t}, \end{aligned} \tag{8}$$

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 and δ_i represent time-fixed and firm-fixed effects, respectively, and standard errors are double-clustered at the month and stock level. $SHOMonth_t$ is subsumed by the time-fixed effects, and $PilotStock_i$ is subsumed by the firm-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_5, which measures the difference-in-difference of the coefficient on the DJF between pilot and non-pilot stocks during the experiment months. We expect b_5 to be positive as we conjecture 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 regression results. The coefficient on the DJF remains significantly negative. Most importantly, b_5 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 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 estimates 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 proxies of the short-sale constraint and other IV-related variables. In addition, we re-estimate the PLS downward jump factor by targeting on idiosyncratic jumps (instead of total return jumps) and examine the performance of the idiosyncratic DJF. Furthermore, we investigate the predictive power of the DJF over longer investment horizons. Finally, we consider a refined version of the PLS approach in the estimation of the DJF. 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 in different ways and test the predictive power of the DJF separately. We explore five different sets of subperiods defined based on the market return, market volatility, business cycle, 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 factor 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. 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 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.

The table also reports the performance of the DJF in subsamples corresponding to below-median and above-median market volatility (Panels C and D), expansion and recession (Panels E and F), pessimistic and optimistic market sentiment (Panels G and H), and randomly defined samples (Panels I and J). [14] Overall, the performance of our estimated DJF is quite robust in 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 show a corresponding decreasing pattern. The long-short portfolio always generates economically large and statistically significant total and abnormal returns, contributed by both legs.

5.2. Size Effect

Fama and French (2008) document that many anomalies are concentrated in microcap stocks, defined as stocks with the market capitalization below the 20^{th} NYSE percentile.

[14] We define expansion and recession periods according to the NBER recession indicator. Following Han (2008), we measure market sentiment by the IV slope of S&P 500 options.

The microcap stocks are on average only about 3% of the market capitalization of the NYSE/AMEX/NASDAQ universe, but 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 into big, small and microcap stocks in each month, according to the 50^{th} and 20^{th} percentiles of the market capitalization of NYSE stocks, and we ask if our results are driven by different size groups. As reported in Section 3.1, the stocks in our sample have liquidly traded options and thus are relatively big stocks. Indeed, based on our cutoffs, about 59% of the stocks are big ones, about 30% are small ones, and only 11% of them are microcaps. For each of the size groups, we repeat our main analysis and report the results in Table 13.[15]

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 size groups perform similarly, with the microcap actually being the weakest. The long-short portfolios have average returns of 1.06%, 1.30% and 0.88%, with Sharpe ratios of 0.93, 1.18 and 0.76 for the big, small, and microcap stocks, respectively. The abnormal returns are also economically large and statistically significant at the 1% level.

5.3. Double-Sorted Portfolios

In the section, we perform double sorts to better control for the effect of other related characteristics on the predictive power of our estimated DJF.

[15] We also construct value-weighted portfolios using all the stocks, and the results (not shown) are similar.

5.3.1. *Short-Sale Constraints*

We show that the predictive power of the DJF is linked to the short-sale constraint in the equity market. It is interesting to see whether the portfolio sorting results continue to hold after controlling for the tightness of short-sale constraint. To this end, we conduct sequential double sorts. In particular, we use institutional ownership ($insthold_{i,t-1}$) 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 the tightness of the short-sale constraint.

Panels A and B of Table 14 report the average monthly returns of the double-sorted portfolios. Within each quintile sorted by $insthold_{i,t-1}$ or $shortint_{i,t-1}$, the average returns exhibit a monotonically decreasing trend as the DJF increases. For example, within the bottom quintile 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, giving rise to an average monthly spread of 1.63% between stocks with the lowest DJF and stocks with the highest DJF. When the institutional ownership increases from the bottom quintile to the top quintile, this spread monotonically decreases from 1.63% to 0.49%. Similarly, when short interests increase from the bottom quintile to the top quintile, the average spread between stocks with the lowest and highest DJF monotonically increases from 0.61% to 1.45%. The double sorting results confirm our previous regression results and provide further evidence that the predictive power of the DJF increases with the tightness of the short-sale constraint in the equity market.

5.3.2. *Volatility-Based Characteristics*

We conduct similar double sorts to check if our previous portfolio sorting results are robust after controlling for the other IV-related variables as well as stock volatility. The first sorting variable we use is the implied volatility slope (ivs), volatility spread (vsp), call and put volatility innovations (Δciv and Δpiv), or historical volatility, and the results are reported in Table 15. We can see that the decreasing relation between the DJF and portfolio return continues to hold within almost all quintiles sorted by these characteristics, and the spreads between the extreme DJF portfolios are highly significant.

5.4. Idiosyncratic Jumps

Bégin, Dorion, and Gauthier (2019) and Kapadia and Zekhnini (2019) both argue that idiosyncratic jumps are important determinants of stock returns. In this subsection, we re-estimate the DJF based on downward idiosyncratic jumps and examine whether the resulting estimates continue to predict future total returns and total return jumps. To this end, we define the idiosyncratic return as the residual term from the seven-factor model (Fama-French five factors plus momentum and illiquidity), and a downward idiosyncratic jump as an idiosyncratic return below -15%.

Table 16 reports the results. Similar to our baseline results, the DJF estimated based on idiosyncratic downward jumps continue to have strong predictive power regarding future total returns and total return jumps. The difference in the total return downward jump probability is about 5.76% between the top and bottom deciles sorted by the DJF estimated using the idiosyncratic jumps. In addition, the long-short portfolio yields an annualized return of 14.88% and an abnormal return of 12.00%, both significant at the 1% level. The annualized Sharpe ratio is 1.07. These results are only slightly weaker than our baseline results obtained when the DJF is estimated using the total return jumps (Table 2). This suggests that the predictive power of the DJF mainly comes from idiosyncratic jumps.

5.5. *Longer Investment Horizons*

In this subsection, we evaluate the performance of the DJF-sorted portfolios over longer investment horizons. Table 17 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 twelve (Panel D) months. Similar to 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 as the DJF increases. All of the long-short portfolios have positive returns and alphas 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.

5.6. *Refining PLS*

As our last robustness check, we follow Light, Maslov and Rytchkov (2017) and adopt a refined version of the PLS methodology. In particular, after estimating the first stage (2), we take the average of $\hat{\lambda}$ over the most recent 12 months, and use this average as the regressor in the second stage (3). The idea of this refinement is to reduce noises from estimating the first stage based on information from one single period.

Table 18 reports the performance of decile portfolios sorted by the DJF estimated using the refined PLS. The results show that there is a 6.5% difference in the probability of downward jumps between the top and bottom deciles. The corresponding long-short portfolio yields an average annualized return of 20.88%, a significantly positive alpha, and an annualized Sharpe ratio of 1.61. Compared to our main results reported in Table 2, the refined PLS estimates indeed lead to better results. One potential downside of this approach is that estimation for any particular month now requires data from the previous 12 months (as opposed to 2 months using the baseline approach), which might present a limitation when the sample period is short or when there are structural breaks in the relation between the IVs and the latent jump factor. Nevertheless, the bottom line is that our baseline PLS estimates can potentially be improved to achieve even better performance.

6. Conclusion

Option prices as represented by the implied volatility (IV) contain information about the underlying stocks. Prior literature often uses a pair of put and call (e.g., with 30-day to mature) out of hundreds of options, which can result in loss of information. In this paper, we take an innovative approach to utilize the entire surface of the implied volatility.

We employ the PLS approach to estimate latent jump factors using information from the entire IV surface. We find that option prices contain information about downward jumps in the underlying stock prices, but not upward jumps. The estimated downward jump factor strongly predicts future probabilities of jumps and stock returns. A zero-investment strategy taking a long position in stocks with the lowest DJF and a short position in stocks with the highest DJF yields an annualized return of 18.36% and a Sharpe ratio of 1.29. We further find that the most relevant information comes from out-of-the-money and at-the-money put option prices, and from both long-term and short-term options. Moreover, the predictability is robust to a number of firm characteristics and is much stronger than that of other option-related variables and in particular IV-related variables documented in the literature. These results highlight the inefficiency of using just a few options with *ad hoc* choices.

One possible explanation for the better predictability of downward jumps compared to upward jumps based on information from option prices is that informed traders use options to circumvent the short-sale constraint in the equity market. Along this line, we would expect stronger predictability for stocks that are subject to tighter short-sale constraint. We use three approaches to test this economic channel, including two proxies for the tightness of the short-sale constraint (short interest and institutional ownership) and one quasi-natural experiment provided by the Pilot Program of Regulation SHO. All three tests support our conjecture and suggest that the incentive of informed investors to circumvent the short-sale constraint in the equity market contributes to the incorporation of negative information into option prices.

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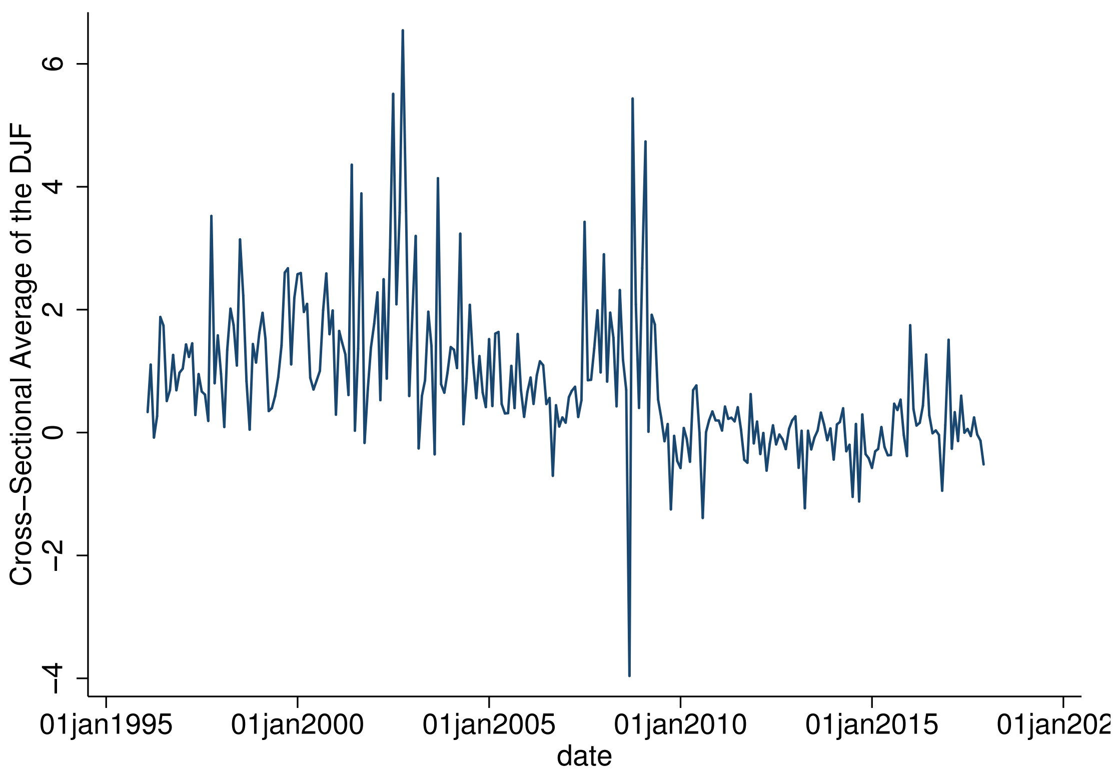

Figure 1: Cross-Sectional Average of the Downward Jump Factor
This figure plots the time series of the cross-sectional average of the DJF estimated with a downward jump threshold of -15%. The sample period is from January 1996 to December 2017.

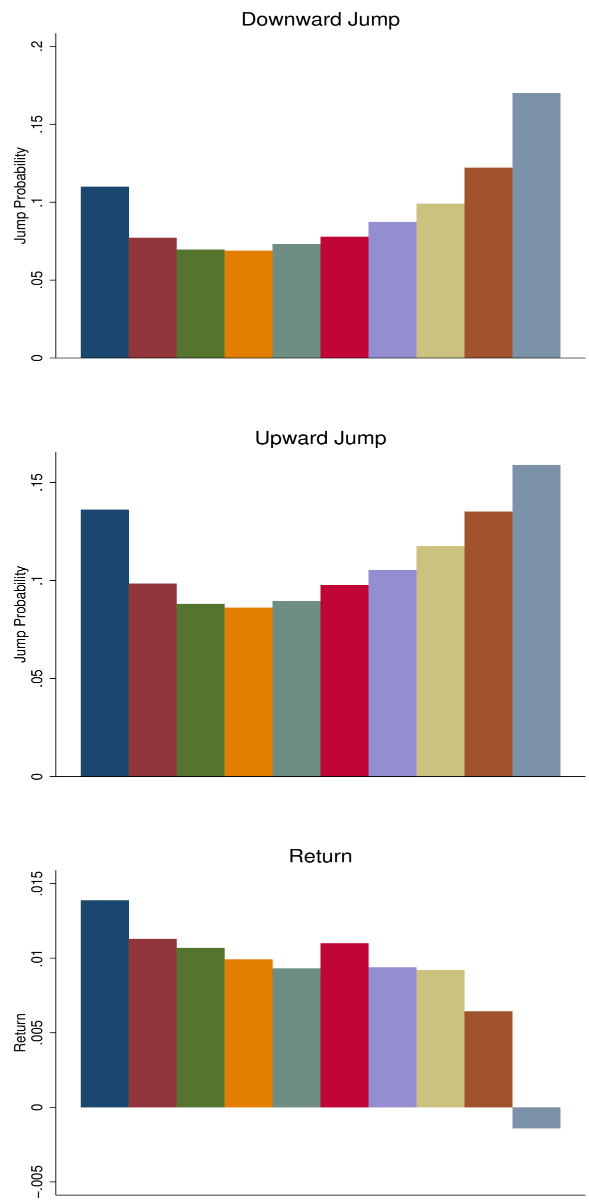

Figure 2: Portfolio Sorts by the Downward Jump Factor
This figure plots the average monthly probabilities of downward and upward jumps as well as the average monthly returns of decile portfolios of stocks sorted by the downward jump factor estimated based on a downward jump threshold of -15%. The sample period is from January 1996 to December 2017.

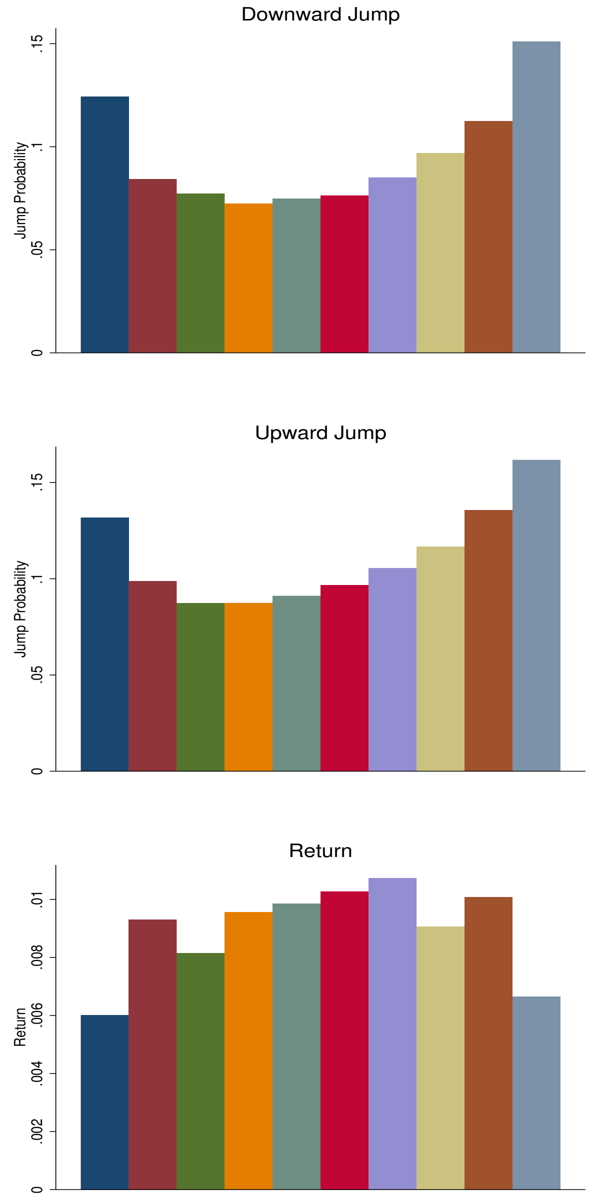

Figure 3: Portfolio Sorts by the Upward Jump Factor
This figure plots the average monthly probabilities of downward and upward jumps as well as the average monthly returns of decile portfolios of stocks sorted by the upward jump factor estimated based on an upward jump threshold of 15%. The sample period is from January 1996 to December 2017.

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 (Panel A) and the entire CRSP sample (Panel B). Firm size is the year-end market capitalization (in billion dollars) 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%	50%	95%	Skewness	Kurtosis
	Panel A: Our Sample							
Size	4,688	3.8909	15.0551	0.1021	0.7565	14.2939	10.7563	154.1576
Book-to-Market	4,688	0.5749	0.7149	0.0695	0.5043	1.3655	-14.0460	614.9061
Profitability	4,688	0.0067	1.8210	-0.2438	0.0172	0.0975	34.1029	1569.5410
Investment	4,688	0.2504	0.6862	-0.0891	0.1313	0.8690	14.8403	343.9049
Illiquidity	4,688	0.0158	0.1033	0.0001	0.0020	0.0390	16.3958	316.2057
	Panel B: Entire CRSP Sample							
Size	11,410	1.8311	9.9912	0.0080	0.1580	6.2220	15.7578	336.9171
Book-to-Market	11,410	0.7027	2.8442	0.0300	0.6209	2.0783	-25.0946	1515.0870
Profitability	11,410	-0.0584	2.1569	-0.4272	0.0105	0.0911	-20.8223	1468.3530
Investment	11,410	0.1888	0.6840	-0.2170	0.0983	0.7744	28.0633	1530.7810
Illiquidity	11,410	1.0939	4.2993	0.0001	0.0407	5.2092	11.5863	204.7458

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 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 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 illiquidity 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 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 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 illiquidity 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/Put and Moneyness

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 downward jump factor estimated based on a downward jump threshold of -15% using implied volatilities of out-of-the-money (OTM) and at-the-money (ATM) put options (Panel A), OTM and ATM call options (Panel B), in-the-money (ITM) put options (Panel C), and ITM call options (Panel D). The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the 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 illiquidity 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: OTM+ATM Put						
DJ Prob	0.1023	0.0824	0.0758	0.0747	0.0755	0.0792	0.0858	0.0977	0.1200	0.1616	-0.0594***
											(0.0060)
UJ Prob	0.1225	0.0961	0.0896	0.0887	0.0915	0.0994	0.1073	0.1195	0.1365	0.1615	-0.0390***
											(0.0039)
Return	0.0115	0.0100	0.0084	0.0087	0.0091	0.0102	0.0107	0.0104	0.0084	0.0022	0.0093***
											(0.0020)
Alpha	0.0025*	0.0019	-0.0019**	-0.0015	-0.0010	0.0001	0.0010	0.0012	0.0003	-0.0042***	0.0067***
	(0.0013)	(0.0015)	(0.0009)	(0.0011)	(0.0008)	(0.0007)	(0.0009)	(0.0010)	(0.0013)	(0.0014)	(0.0016)
					Panel B: OTM+ATM Call						
DJ Prob	0.1009	0.0791	0.0779	0.0750	0.0769	0.0816	0.0915	0.1008	0.1195	0.1520	-0.0512***
											(0.0056)
UJ Prob	0.1154	0.0896	0.0849	0.0880	0.0944	0.1032	0.1103	0.1243	0.1389	0.1636	-0.0481***
											(0.0052)
Return	0.0078	0.0093	0.0074	0.0086	0.0095	0.0101	0.0097	0.0107	0.0096	0.0069	0.0008
											(0.0024)
Alpha	-0.0014	0.0011	-0.0020**	-0.0009	-0.0005	-0.0002	0.0001	0.0013	0.0014	-0.0003	-0.0011
	(0.0011)	(0.0014)	(0.0008)	(0.0009)	(0.0010)	(0.0008)	(0.0010)	(0.0012)	(0.0012)	(0.0018)	(0.0022)

	Low	2	3	4	5	6	7	8	9	High	Low-High
					Panel C: ITM Put						
DJ Prob	0.1036	0.0830	0.0799	0.0770	0.0756	0.0825	0.0883	0.1000	0.1171	0.1481	-0.0445***
											(0.0064)
UJ Prob	0.1212	0.0919	0.0911	0.0868	0.0936	0.1004	0.1086	0.1211	0.1346	0.1633	-0.0421***
											(0.0046)
Return	0.0092	0.0073	0.0086	0.0070	0.0103	0.0097	0.0110	0.0104	0.0086	0.0076	0.0016
											(0.0022)
Alpha	-0.0006	-0.0021**	0.0000	-0.0035***	0.0005	-0.0005	0.0017	0.0012	0.0011	0.0008	-0.0014
	(0.0014)	(0.0009)	(0.0018)	(0.0009)	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.012)	(0.0016)	(0.0022)
					Panel D: ITM Call						
DJ Prob	0.1036	0.0829	0.0799	0.0770	0.0757	0.0824	0.0882	0.1001	0.1172	0.1480	-0.0445***
											(0.0064)
UJ Prob	0.1211	0.0919	0.0911	0.0868	0.0935	0.1005	0.1087	0.1210	0.1347	0.1633	-0.0422***
											(0.0046)
Return	0.0091	0.0074	0.0086	0.0069	0.0104	0.0097	0.0110	0.0104	0.0086	0.0076	0.0015
											(0.0022)
Alpha	-0.0005	-0.0020**	-0.0002	-0.0036***	0.0005	-0.0005	0.0017	0.0012	0.0011	0.0008	-0.0013
	(0.0014)	(0.0009)	(0.0016)	(0.0009)	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0012)	(0.0016)	(0.0022)

Table 5: Portfolio Sorts by the Downward Jump Factor Estimated Based on 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 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 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 illiquidity 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.

	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.

	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 by Regression

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***	
	(0.0006)	(0.0006)		(0.0008)	
bm		0.0011	0.0012		
		(0.0009)	(0.0009)		
$cash$		0.0003	0.0003		
		(0.0011)	(0.0011)		
Δmom		0.0005	0.0005		
		(0.0007)	(0.0007)		
$\Delta nanalyst$		-0.0004	-0.0004		
		(0.0003)	(0.0003)		
ear		0.0010**	0.0011***		
		(0.0004)	(0.0004)		
$mom1m$		-0.0018*	-0.0019*		
		(0.0010)	(0.0011)		
$nincr$		0.0004	0.0005		
		(0.0003)	(0.0003)		
$rdmve$		0.0034**	0.0035**		
		(0.0015)	(0.0015)		
$retvol$		-0.0021	-0.0026		
		(0.0022)	(0.0023)		
$turn$		-0.0003	-0.0006		
		(0.0008)	(0.0008)		
$turnvol$		-0.0003	-0.0002		
		(0.0007)	(0.0007)		
ivs				0.0008	0.0027***
				(0.0005)	(0.0005)
vsp				-0.0008	-0.0005
				(0.0006)	(0.0006)
Δciv				0.0011*	0.0014**
				(0.0006)	(0.0005)
Δpiv				0.0002	-0.0011*
				(0.0005)	(0.0005)
$osvolume$				-0.0012**	-0.0016***
				(0.0006)	(0.0006)
$cpvolume$				0.0007***	0.0008***
				(0.0003)	(0.0003)
$cpoi$				-0.0002	-0.0003
				(0.0004)	(0.0004)
Cons	0.0090**	0.0122***	0.0124***	0.0089**	0.0090**
	(0.0039)	(0.0046)	(0.0046)	(0.0039)	(0.0039)

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

This table reports the average slope coefficients from (1) monthly cross-sectional regressions of the stock return on the downward jump factor (DJF) estimated from the previous month, the lagged value of the higher-than-median short interest dummy ($shortintH$), and their interaction, and (2) monthly cross-sectional regressions of the stock return on the 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 Ownership, and Future Stock Return

This table reports the average slope coefficients from (1) monthly cross-sectional regressions of the stock return on the downward jump factor (DJF) estimated from the previous month, the lagged value of the lower-than-median institutional ownership dummy ($insthold L$), and their interaction, and (2) monthly cross-sectional regressions of the stock return on the downward jump factor (DJF) estimated from the previous month, the lagged value of the institutional ownership ($insthold$), and their interaction. The sample period is from January 1996 to December 2017. The jump factors and the institutional ownership 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)
$insthold L$	-0.0013	
	(0.0011)	
$DJF \times insthold L$	-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 downward jump factor (DJF) and its interaction terms with the pilot stock dummy ($PilotStock$) and the Regulation SHO month dummy ($SHOMonth$), controlling for the time-fixed and firm-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 double-clustered at the month and 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	-0.0023**
	(0.0010)
$DJF \times PilotStock$	-0.0011
	(0.0010)
$DJF \times SHOMonth$	-0.0010
	(0.0018)
$PilotStock \times SHOMonth$	0.0045
	(0.0016)
$DJF \times PilotStock \times SHOMonth$	0.0044**
	(0.0018)
Cons	0.0126***
	(0.0001)
Time-Fixed Effect	Yes
Firm-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 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 NBER recession indicator. 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 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 illiquidity factor of Pástor and Stambaugh (2003). Newey-West 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 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} percentiles of the market capitalization of NYSE stocks. The portfolios are rebalanced monthly based on the 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 illiquidity 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: 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 returns of double-sorted portfolios. The stocks are first sorted by their institutional ownerships (Panel A) or short interests (Panel B) into five quintiles. Within each quintile, the stocks are further sorted by the 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 with five lags 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 Ownership and the DJF

		Institutional Ownerships				
		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 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 Double-Sorted by the Downward Jump Factor and Volatility-Based Characteristics

This table reports the average monthly returns of double-sorted portfolios. The stocks are first sorted by their implied volatility slope (Panel A), volatility spread (Panel B), call and put implied volatility innovations (Panels C and D), or historical volatility (Panel E) into five quintiles. Within each quintile, the stocks are further sorted by the 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 with five lags are reported in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Panel A: Sorting by Implied Volatility Slope and the DJF

		Implied Volatility Slope				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0111	0.0098	0.0102	0.0124	0.0155
	Q2	0.0073	0.0089	0.0085	0.0103	0.0176
	Q3	0.0068	0.0084	0.0081	0.0100	0.0146
	Q4	0.0031	0.0070	0.0090	0.0108	0.0135
	High	-0.0067	0.0016	0.0083	0.0077	0.0106
	Low-High	0.0178***	0.0082***	0.0019	0.0048**	0.0049**
		(0.0027)	(0.0024)	(0.0022)	(0.0022)	(0.0022)

Panel B: Sorting by Volatility Spread and the DJF

		Volatility Spread				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0141	0.0128	0.0109	0.0109	0.0130
	Q2	0.0126	0.0105	0.0096	0.0099	0.0087
	Q3	0.0124	0.0109	0.0107	0.0088	0.0088
	Q4	0.0084	0.0115	0.0088	0.0086	0.0064
	High	0.0012	0.0058	0.0049	0.0054	-0.0011
	Low-High	0.0129***	0.0070***	0.0060***	0.0056***	0.0142***
		(0.0021)	(0.0018)	(0.0018)	(0.0020)	(0.0024)

Panel C: Sorting by Call Implied Volatility Innovations and the DJF

		Call Implied Volatility Innovations				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0082	0.0113	0.0123	0.0135	0.0182
	Q2	0.0064	0.0101	0.0105	0.0113	0.0133
	Q3	0.0071	0.0085	0.0096	0.0124	0.0131
	Q4	0.0040	0.0079	0.0097	0.0114	0.0114
	High	-0.0036	0.0050	0.0066	0.0053	0.0015
	Low-High	0.0118***	0.0062***	0.0057***	0.0083***	0.0167***
		(0.0020)	(0.0019)	(0.0017)	(0.0021)	(0.0023)

Panel D: Sorting by Put Implied Volatility Innovations and the DJF

		Put Implied Volatility Innovations				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0129	0.0115	0.0141	0.0121	0.0127
	Q2	0.0105	0.0098	0.0102	0.0108	0.0107
	Q3	0.0097	0.0108	0.0100	0.0098	0.0084
	Q4	0.0095	0.0101	0.0101	0.0088	0.0061
	High	0.0015	0.0065	0.0072	0.0040	-0.0027
	Low-High	0.0114***	0.0051***	0.0069***	0.0080***	0.0154***
		(0.0025)	(0.0019)	(0.0016)	(0.0019)	(0.0022)

Panel E: Sorting by Historical Volatility and the DJF

		Historical Volatility				
		Q1	Q2	Q3	Q4	Q5
DJF	Low	0.0115	0.0128	0.0135	0.0123	0.0108
	Q2	0.0102	0.0110	0.0106	0.0111	0.0095
	Q3	0.0098	0.0103	0.0113	0.0098	0.0075
	Q4	0.0100	0.0111	0.0100	0.0082	0.0020
	High	0.0099	0.0089	0.0073	0.0033	-0.0085
	Low-High	0.0016	0.0038***	0.0062***	0.0090***	0.0192***
		(0.0011)	(0.0011)	(0.0015)	(0.0024)	(0.0016)

Table 16: 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 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 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 illiquidity 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
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 17: 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 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 twelve (Panel D) months. The sample period is from January 1996 to December 2017. The portfolios are rebalanced monthly based on the 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 illiquidity 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: 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: Twelve 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)

Table 18: Portfolio Sorts by the Downward Jump Factor Based on Refined PLS

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 downward jump factor estimated based on a downward jump threshold of -15% and a refined version of PLS. The refined PLS takes the average of $\hat{\lambda}$ in (2) over the most recent 12 months as the regressor in (3). The sample period is from January 1997 to December 2017, with January 1996 to December 1996 being left out as the initial training period. The portfolios are rebalanced monthly based on the 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 illiquidity 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
DJ Prob	0.1091	0.0763	0.0679	0.0687	0.0749	0.0781	0.0882	0.1012	0.1266	0.1740	-0.0649***
											(0.0059)
UJ Prob	0.1376	0.0987	0.0878	0.0858	0.0902	0.0957	0.1069	0.1179	0.1367	0.1587	-0.0211***
											(0.0046)
Return	0.0147	0.0124	0.0107	0.0099	0.0089	0.0098	0.0093	0.0082	0.0063	-0.0028	0.0174***
											(0.0022)
Alpha	0.0056***	0.0032***	0.0009	0.0002	-0.0010	0.0002	0.0001	-0.0003	-0.0012	-0.0085***	0.0141***
	(0.0013)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0017)	(0.0019)