Characterizing Idiosyncratic Jump Risk: An Option-Based Approach*

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Abstract

This paper uses an option-based approach to characterize idiosyncratic jump risk for a large number of firms over a twenty-year period. We find that idiosyncratic jump risk carries a significant negative risk premium. It correlates with certain firm characteristics and can explain part of the idiosyncratic volatility puzzle. Moreover, we show that the average idiosyncratic jump risk of individual firms is a systematic risk factor that affects the cross-section of stock return, even after controlling for the aggregate market jump risk. These results suggest that idiosyncratic jump risk has important asset pricing implications.

JEL Classification: G12, G14

Keywords: Idiosyncratic Jump Risk; Equity Options; Cross-Section of Stock Returns.

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1 Introduction

While idiosyncratic jumps should not be priced according to the classical asset pricing theory, recent studies find that they are associated with significant risk premiums.[1] This paper contributes to the literature by using a new measure to estimate the idiosyncratic jump risk of individual firms. With this new measure, we quantify the daily idiosyncratic jump risk for approximately five thousand firms over a twenty-year period. This allows us to construct the largest sample by far to study the idiosyncratic jump risk premium.

The key to constructing such a large sample is that our idiosyncratic jump risk measure is based on an equity option strategy. The return of this strategy is purely affected by the jump risk of the underlying firm and thus can be used as an idiosyncratic jump risk measure. This strategy relies on relatively few assumptions and is very simple to implement. We apply it to every firm that has traded options over the period of 1996 to 2016. This greatly expands our sample and allows us to be the first to conduct a comprehensive characterization of the idiosyncratic jump risk of individual firms. Moreover, because our measure is based on options, we are the first to study the forward-looking idiosyncratic jump risk of individual firm.

We obtain several new key findings. First, we confirm that idiosyncratic jump risk earns a negative risk premium. The magnitude is estimated to be approximately -8.8% per month. The negative sign suggests that investors dislike idiosyncratic jumps and demand securities that can hedge idiosyncratic jumps. Consistent with this argument, we find that the option strategy that tracks the idiosyncratic jump risk does pay during the bad economic conditions.

Second, we find the idiosyncratic jump risk premium is of larger magnitude for smaller firms, firms with higher idiosyncratic volatility, and firms with lower liquidity.

[1]See, for example, Xiao and Zhou (2015), Bégin, Dorion, and Gauthier (2016), and Kapadia and Zekhnini (2016).

This suggests that the idiosyncratic jump risk is correlated with certain firm characteristics. We also find controlling for the idiosyncratic jump risk help to explain the idiosyncratic volatility puzzle.

Third, we show that the average idiosyncratic jump risk affects the cross-section of stock returns. The average idiosyncratic jump risk explains approximately 20% of total variations of the idiosyncratic jump risk of individual firms, suggesting that it is a common component. When sorting stocks based on the sensitivity to the average idiosyncratic jump risk, we find that the stocks with higher sensitivity earn lower subsequent returns. This result strongly suggests that the common idiosyncratic jump risk enters the pricing kernel.

Our paper is closely related to three strands of literature. First, it is related to the recent literature which uses parametric models to study the idiosyncratic jump and its risk premium. (See, for example, Xiao and Zhou (2015), Bégin, Dorion, and Gauthier (2016)). While parametric models are informative about the economic channel that are associated with the idiosyncratic jump risk, the computational burden could limit the sample size. This paper uses a non-parametric approach to track the idiosyncratic jump risk of individual firm. We estimate the idiosyncratic jump risk for a large number of firms.

Our paper is also related to the literature which uses non-parametric methods to study idiosyncratic jumps (See, for example, Bollerslev, Li, and Todorov (2016), Bollerslev, Li, and Zhao (2016), and Kapadia and Zekhnini (2016)). Those papers use high-frequency data or the price data to identify realized price jumps. Thus those identified jumps are backward-looking. On the contrary, our measure is based on equity options. We study the forward-looking idiosyncratic jump risk of individual firm.

Finally, our paper is related to the literature which studies the impact of market jump risk. Previous papers have documented that the jump risk on the market level is an important risk factor. (See, for example, Bates (1996), Pan (2002), Johannes

(2004), Broadie, Chernov, and Johannes (2007), Bates (2008), Santa-Clara and Yan (2010), Yan (2011), Bollerslev and Todorov (2011), Drechsler and Yaron (2011), Christoffersen, Jacobs, and Ornthanalai (2012), Bollerslev, Todorov, and Xu (2015), and Cremers, Halling, and Weinbaum (2015)) We contribute by showing that the average idiosyncratic jump risk is another systematic risk factor affecting the asset prices.

The remainder of this paper proceeds as follows. Section 2 discusses the methodology that we used to measure the idiosyncratic jump risk of individual firms. Section 3 describes the data and the sample statistics. Section 4 studies the idiosyncratic jump risk of individual firms and its cross-sectional distribution. Section 5 analyzes the common component of the idiosyncratic jump risk and tests its asset pricing implications. Finally, section 6 concludes.

2 Measuring Idiosyncratic Jump Risk

We use the return on a Delta-neutral, Vega-neutral, and Gamma-positive equity option portfolio to track the idiosyncratic jump risk of the underlying firm. The intuition is that such a portfolio tracks large movements in underlying prices while hedging the small price and volatility changes. Cremers, Halling, and Weinbaum (2015) construct this portfolio using S&P 500 futures options to measure the jump risk of the aggregate market. We apply their approach to equity options to measure the jump risk of individual stocks.

Specifically, for each stock on each day, we rank all its calls and puts based on moneyness.[2] Then we choose the call and put that are the closest to at-the-money (ATM) to formulate an ATM delta-neutral straddle. Following Coval and Shumway

[2]The moneyness is defined as the strike to the underlying price ratio.

(2001), the weights of the calls and puts are calculated by solving the following equations:

$$\begin{aligned} &\theta_{\text{Call},t} + \theta_{\text{Put},t} = 1 \\ &\theta_{\text{Call},t} \times \Delta_{\text{Call},t} + \theta_{\text{Put},t} \times \Delta_{\text{Put},t} = 0 \end{aligned} \tag{1}$$

where $\Delta_{\text{Call},t}$ is the Delta of the call option in the Black-Scholes model and $\Delta_{\text{Put},t}$ is the Delta of the put option in the Black-Scholes model.[3]

For each stock on each day, we apply equation (1) to the nearest-month options and the second nearest-month options, yielding to a short-term straddle and a long-term straddle. Denoting the weights for the short-term straddle by $(\theta^s_{\text{Call},t}, \theta^s_{\text{Put},t})$ and the weights for the long-term straddle by $(\theta^l_{\text{Call},t}, \theta^l_{\text{Put},t})$, we could express the return on the straddles as follows:

$$\begin{aligned} \text{Ret}^s_{\text{Straddle},t} &= \theta^s_{\text{Call},t} \times \text{Ret}^s_{\text{Call},t} + \theta^s_{\text{Put},t} \times \text{Ret}^s_{\text{Put},t} \\ \text{Ret}^l_{\text{Straddle},t} &= \theta^l_{\text{Call},t} \times \text{Ret}^l_{\text{Call},t} + \theta^l_{\text{Put},t} \times \text{Ret}^l_{\text{Put},t} \end{aligned} \tag{2}$$

where $\text{Ret}^s_{\text{Straddle},t}$ denotes the return on the short-term ATM straddle, $\text{Ret}^s_{\text{Call},t}$ denotes the return on the short-term ATM call option, and $\text{Ret}^s_{\text{Put},t}$ denotes the return on the short-term ATM put option. Similarly, $\text{Ret}^l_{\text{Straddle},t}$, $\text{Ret}^l_{\text{Call},t}$, and $\text{Ret}^l_{\text{Put},t}$ denote the return on the long-term ATM straddle, call option, and put option respectively.

Next, on each day t, we construct the Delta-neutral, Vega-neutral, and Gamma-positive option portfolio by longing γ_t contract of the short-term straddle and shorting one contract of the long-term straddle, where γ_t is calculated by solving the following equation:

$$\gamma_t \times \nu^s_t - \nu^l_t = 0 \tag{3}$$

[3] While using the Greeks in the Black-Scholes model seems inconsistent with the jump assumption, existing papers have shown that the impact of this assumption is small. (Cremers, Halling, and Weinbaum (2015))

where ν_t^s denotes the Vega of the short-term straddle at time t and ν_t^l denotes the Vega of the long-term straddle, and ν_t^s and ν_t^l are calculated as follows:

$$\begin{aligned} \nu_t^s &= \theta_{\text{Call},t}^s \times \nu_{\text{Call},t}^s + \theta_{\text{Put},t}^s \times \nu_{\text{Put},t}^s \\ \nu_t^l &= \theta_{\text{Call},t}^l \times \nu_{\text{Call},t}^l + \theta_{\text{Put},t}^l \times \nu_{\text{Put},t}^l \end{aligned} \tag{4}$$

where $\nu_{\text{Call},t}^s$, $\nu_{\text{Put},t}^s$, $\nu_{\text{Call},t}^l$, and $\nu_{\text{Put},t}^l$ are the Vega of the short-term ATM call, the short-term ATM put, the long-term ATM call, and the long-term ATM put respectively. Because short-term options have larger Gamma than long-term options, equation (3) ensures that the Gamma of the resulting option portfolio is positive.

Using equation (3), the return on the Delta-neutral, Vega-neutral, and Gamma-positive option portfolio, or the idiosyncratic jump option portfolio can be written as follows:

$$\text{Ret}_{\text{Idio Jump},t} = \gamma_t \times \text{Ret}_{\text{Straddle},t}^s - \text{Ret}_{\text{Straddle},t}^l \tag{5}$$

In the empirical section, we calculate the return on the idiosyncratic jump portfolio for each stock on each day. Thus, we get a daily measure for the idiosyncratic jump risk for each stock.

3 Sample

This section describes the data source and the procedure we follow to construct the sample. The equity option data is from OptionMetrics. We include all options in OptionMetrics and impose the following filters: (1) the bid price, ask price, implied volatility, and all option Greeks are non-missing, (2) the open interest is positive, (3) the bid price is positive and less than the offer price. (4) the bid-ask price satisfy the no-arbitrage condition, (5) the term to maturity is larger or equal to 14 days, (6) the option price, which is defined as the average of the bid and ask price, is greater than

\$0.50, (7) the moneyness is between 0.96 to 1.04, and (8) the maturity is less than six months.[4]

The equity data is from CRSP. We include all common shares (i.e. the share code equals 10 or 11) listed on the AMEX, NASDAQ, or NYSE. For each stock, we collect its close prices, outstanding number of shares, and daily returns.

We merge the equity and option data based on the permno and the ticker information. Our final sample consists of 3,087,639 number of observations over 5,116 days ranging from January, 1996 to April, 2016.

Table 1 reports the summary statistics of the short-term and long-term options in the sample. On average, the return on the call option is slightly positive and the average return on the put option is negative. The average relative bid-ask spread is approximately 15% for short-term options and 11% for long-term options, suggesting the equity option market is quite illiquid. The average maturity is approximately 1 month (36 days) for short-term options and approximately 3 months (93 days) for long-term options.

Equity options are illiquid (Vijh (1990), Jameson and Wilhelm (1992), Cetin, Jarrow, Protter, and Warachka (2006), Goyal and Saretto (2009), Engle and Neri (2010), Cao and Wei (2010), Christoffersen, Goyenko, Jacobs, and Karoui (2015), and Choy and Wei (2016)). To further check the effect of illiquidity, we choose five liquidity measures and sort options based on each measure. Table 2 shows the distribution of the number of options for each liquidity measure. For both short-term and long-term calls and puts, the number of options in the least liquid brackets is small relative to the total sample size. Thus, we conclude that the liquidity issue of equity options does not have a large impact on our selected options.

[4]The last two restrictions are mainly to ensure that the options that are selected are close to ATM and the difference between the maturity of the short-term and long-term options is not too large. Relaxing those restrictions yields similar results.

4 The Idiosyncratic Jump Risk of Individual Firms

This section presents our results on the idiosyncratic jump risk of individual firms. We first demonstrate that our option-based idiosyncratic jump risk measure identifies realized jumps in the underlying stock price. Then we study the statistical properties of the idiosyncratic jump risk premium. We further investigate the cross-sectional relationship between the idiosyncratic jump risk premium and the firm characteristics. Finally, we check whether the idiosyncratic jump can help explain certain return anomaly.

4.1 Identifying Idiosyncratic Jump Risk

If our option-based idiosyncratic jump risk measure captures the jump risk of the underlying stock, then it should be consistent with the realized jump of that stock. For example, our measure should peak when a realized jump occurs because our measure is positively correlated with the jump probability of the underlying stock.

Figure 1 plots the idiosyncratic jump risk measure of Apple Inc., along with realized market price jumps (jumps of the S&P 500) and the idiosyncratic jumps of Apple stock. The realized jumps are calculated using daily prices with Lee and Mykland (2008) method.[5] The top panel shows the portfolio return with the realized jumps of Apple and the bottom one shows the realized jumps of S&P 500.

The figure shows that the return on the idiosyncratic jump portfolio aligns well with the jumps in Apple. Our measure in general peaks whenever a jump in Apple occurred, suggesting our measure does capture the jump of the underlying stock. The bottom panel shows that our measure also captures some of the market jumps. This reflects the fact that jumps of individual stock might be caused by the aggregate jump of the market. However, the stock of Apple experience more jumps than S&P 500, so most

[5] The details of the empirical implication are given in Appendix A.1.

of Apple's jump are idiosyncratic. Based on this observation, we conclude that our measure is mainly driven by the firm's idiosyncratic jump risk instead of the market jump risk.

4.2 The Idiosyncratic Jump Risk Premium

Table 3 reports the summary statistics of the return on the idiosyncratic jump portfolio. It reports the statistics in each year as well as the statistics over the whole sample period.

In total, we estimate the idiosyncratic jump risk for approximately 5,000 firms. This is by far the largest sample that has been studied in the existing literature. On average, there are around 1,500 firms included in our sample each year. There is no significant pattern for the number of firms in each year. The available observation for each firm steadily increases over the period 1996 to 2016.[6]

The first result in Table 3 is that the average return on the idiosyncratic jump risk portfolio is negative in most of the years as well as in the overall sample period. We can reject the null hypothesis that the mean is equal to zero. The median confirms this conclusion as it is also negative in all years. This suggests that the idiosyncratic jump risk is priced with a negative risk premium. In addition, we find the idiosyncratic jump risk premium could be large as it has large extreme values and large kurtosis.

Overall, our results show that idiosyncratic jump bears significant risk premium. The results are consistent with existing papers which study the idiosyncratic jump risk in a small sample. We confirm their findings in a much larger sample.

[6]The number of observations drops in 2016 because there are only four months included in 2016.

4.3 The Idiosyncratic Jump Risk Premium in Sub-Samples

The negative return on the idiosyncratic jump portfolio suggests that investors would like to pay to hold the idiosyncratic jump risk portfolio. One potential reason is that those portfolios can provide valuable hedges against downward idiosyncratic jumps. To check this argument, we split the sample based on the sign of the underlying stock return and calculate the return on the idiosyncratic jump risk portfolio in both samples. If those portfolios indeed provide valuable hedges, then the return on the portfolio should be higher when the underlying return is negative than when the underlying return is positive.

The sub-sample results are reported in Table 4. In total, there are 1,528,591 number of observations in the positive underlying return sample and 1,503,651 number of observations in the negative return sample.[7] Thus, the number of observations are relatively equal in both samples. When we calculate the average return on the idiosyncratic jump risk portfolio, we find that the return is higher (-0.38%) when the underlying stock return is negative than when the underlying stock return is positive (-0.41%). This shows that our idiosyncratic jump security indeed pays when negative return occurs and thus supports the hedge story. We find the same pattern holds in most of the years.

4.4 The Idiosyncratic Jump Risk Premium and Firm Characteristics

After investigating the idiosyncratic jump risk premium in different years, we now turn to study its cross-sectional distribution. The objective is to study if some firm bears more idiosyncratic jump risk premium than others.

[7] On each day, we classify every stock based on the sign of its return on that day. If the stock has a positive return, then it is classified to the positive underlying return sample. If it has a negative return, then it is classified to the negative underlying return sample. Thus the positive (negative) return sample is a panel data which contains all the positive (negative) return days of all stocks.

We consider seven stock characteristics in total. They are the stock return, stock price, dollar volume, realized volatility, realized skewness, realized kurtosis, the industry that the stock belongs to, stock size, idiosyncratic volatility, and stock illiquidity.[8] For each characteristic in each month, we sort the stocks into ten bins based on the stock characteristic in that month. Then for each bin, we calculate the average idiosyncratic jump risk premium in that month as well as the average idiosyncratic jump risk premium in next month. We examine the contemporaneous relationship between the stock characteristic with the average idiosyncratic jump risk premium as well as the out-of-sample relationship (i.e., the relationship between the current stock characteristic with the average idiosyncratic jump risk premium in next month).

Table 5 reports the unconditional cross-sectional distribution of the idiosyncratic jump risk premium. Except for the industry, portfolio 1 means the portfolio with the lowest value and the portfolio 10 means the portfolio with the highest value.[9] The contemporaneous relationship is reported in the top panel. We find that there is a monotonic relationship between the firm's idiosyncratic jump risk premium with the average stock price, dollar volume, realized volatility, market size, idiosyncratic volatility, and stock liquidity. The relationship is consistent with economic intuitions. For example, because stocks with lower prices, smaller trade volume or market size, and higher volatility or higher illiquidity tend to have larger idiosyncratic jump probabilities, those stocks should have larger idiosyncratic jump risk premium.

On the contrary, we find that there is a U-shape between the idiosyncratic jump risk premium with stock return, realized skewness, and realized kurtosis. This suggests that the idiosyncratic jump risk premium is related to both positive and negative price jumps.

[8] The definition of the idiosyncratic volatility and the illiquidity are given in the Appendix A.2 and A.3 respectively.

[9] For industry, 1 means the consumer non-durables industry, 2 means the consumer durables industry, 3 means the manufacturing industry, 4 means the energy industry, 5 means the high tech industry, 6 means the telecoms industry, 7 means the wholesale and retail industry, 8 means the health-care industry, 9 means the utility industry, and 10 means other industries. The 10 industry codes are obtained on Kenneth French's website.

For the industry, the overall results suggest that the idiosyncratic jump risk premium is of larger magnitude for stocks in non-durable industry (industry 1), in the health-care industry (industry 8), and in the other industries (such as the finance industry, industry 10). This result is consistent with the fact that investor pays more for the stocks that in more volatile industries.

We conduct several additional tests to verify the contemporaneous relationship. The bottom panel reports the out-of-sample relationship between the idiosyncratic jump risk premium and firm characteristics. We find most of the contemporaneous relationship in the top panel also holds out-of-sample.[10]

Table 6 reports a Fama-MacBeth (Fama and MacBeth (1973)) type of regression where the idiosyncratic jump risk premium is regressed against the firm size, the idiosyncratic volatility, and stock illquidity. We find the coefficients in front of all the selected firm characteristics are significant, even after controlling for several other variables. This supports previous findings. Moreover, for each characteristics, Figure 2 and 3 plot the average and the cumulative return on the portfolio 1 and portfolio 10, where the portfolios are the ones used in Table 5. For the average return, we find that the return on the portfolio with higher idiosyncratic jump risks has a larger (more negative) risk premium, which is in line with previous findings. Interestingly, Figure 2 shows the idiosyncratic risk premium first increases and even becomes to positive in the financial crisis. This time-series pattern is consistent with the sub-sample statistics shown in Table 4. For the cumulative returns, Figure 3 shows the difference between the return on the firms with the lowest idiosyncratic jump risk premium and the ones with the highest idiosyncratic jump risk premium is quite large. It shows that the return on the portfolio which has highest idiosyncratic jump risk decrease below to -10% rapidly, while the return on the portfolio which has lowest idiosyncratic jump risk only moves around 0%.

[10]The cross-sectional statistics are exactly same for the industry portfolio in two panels because most of the firm is in the same industry as the one in previous month.

In sum, we find that the idiosyncratic jump risk premium is related to certain firm characteristics. Given that those characteristics have been used in the studies for the arbitrage risk (Lakonishok, Shleifer, and Vishny (1994), Shleifer and Vishny (1997), and Pontiff (2006)) or the idiosyncratic risk (Spiegel and Wang (2005) and Ang, Hodrick, Xing, and Zhang (2006)), it would be interesting to further study their relationship with the idiosyncratic jumps. Here we provide some preliminary empirical evidence. We will leave the detailed study for future work.

4.5 Idiosyncratic Jump Risk and the Cross-Section of Stock Returns

Now that we have established that the idiosyncratic jump risk bears a significant risk premium, we proceed to study its asset pricing implication. This section focuses on the relationship between the idiosyncratic jump risk and the cross-section of stock returns.

Our empirical procedure is as follows. On each month, we sort stocks into five quintile portfolios based on their average monthly idiosyncratic jump risk premiums. Then we calculate the return in the next month for each of the five portfolio. We control for the Fama-French 3-factors (Fama and French (1993)) and the momentum factor (Carhart (1997)) when examining the alpha. If the idiosyncratic jump risk affects the stock returns, then there would be a monotonic relationship between the return on the sorted portfolios with its idiosyncratic jump risk premium and the alphas should be significant.

Table 7 reports the results. First, we find the average return is decreasing from portfolio 1 to portfolio 5, suggesting that the firms with high idiosyncratic jump risk earn low returns. The difference between the return on portfolio 5 and the one of portfolio 1 is also significantly negative. The pattern holds after controlling for the market return, the Fama-French 3 factors, and the Cahart 4 factors. These results confirm that there is a negative market price of risk associated with idiosyncratic jumpss. Our estimates show that longing portfolio 5 and shorting portfolio 1 generates about -0.6% return per day.

After establishing that the idiosyncratic risk is priced, we study whether it could help to explain other return anomalies. We focus on the idiosyncratic volatility puzzle given the close relationship between the idiosyncratic jump risk and the idiosyncratic volatility risk.

Table 8 reports the value-weighted return on double-sorted portfolios on both idiosyncratic jump risks and idiosyncratic volatilities. We find the difference between the return of high idiosyncratic volatility portfolio with the one of low idiosyncratic volatility portfolios becomes insignificant in three of the five idiosyncratic jump quintiles. Thus, idiosyncratic jump risk premiums can explain part of the idiosyncratic volatility risk premium, which is consistent with the fact that the price changes contain both the diffusive part and the jump part. On the other hand, idiosyncratic volatility risk premium cannot completely explain the idiosyncratic jump risk premium, as the return differences between the two extreme portfolios are still significant in three of the five idiosyncratic volatilities quintiles. Overall, the result shows that the idiosyncratic jump risk help to explain part of the idiosyncratic volatility risk.

5 The Commonality in Idiosyncratic Jump Risk

Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) documents that the idiosyncratic volatilities of different firms share a common component and this common component affects the cross-section of stock returns. Here we check if the idiosyncratic jump risks of different firms also have a common component.

To motivate the common component of the idiosyncratic jump risk of different firms, Figure 4 plots the time series of the annual idiosyncratic jump risk of five portfolios that are sorted based on the firm size and five portfolios that sorted are based on the industry of the firm. Both panels show that the general trend of the idiosyncratic jump risk of different portfolios is very similar. This motives us to focus on the cross-sectional mean of the idiosyncratic jump risk of different firms.

5.1 Defining the Common Idiosyncratic Jump Risk

The common idiosyncratic jump (CIJ) is defined as the cross-sectional mean of the idiosyncratic jump risk of different firms. The specific formula is as follows:

$$\text{CIJ}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{Adjusted Idiosyncratic Jump Risk}_{i,t} \tag{6}$$

where N_t is the total number of stocks in month t and Adjusted Idiosyncratic Jump $\text{Risk}_{i,t}$ is the adjusted idiosyncratic jump risk of stock i. The adjustment is to remove the impact of the market jump risk on the firm's idiosyncratic jump risk. Adjusted Idiosyncratic Jump $\text{Risk}_{i,t}$ is defined as follows:[11]

$$\begin{aligned} \text{Idio. Jump Risk}_{i,t} &= \alpha_i + \beta_i \times \text{Market Jump Risk}_t + \epsilon_{i,t} \\ &= \beta_i \times \text{Market Jump Risk}_t + \text{Adj. Idio. Jump Risk}_{i,t} \end{aligned} \tag{7}$$

Market Jump Risk is estimated by applying the methodology in Section 2 on S&P 500 index options. We run the regression (7) for every stock in every month. Because the intercept also contains relevant information, we define the adjusted idiosyncratic jump risk as the residuals plus the intercept.[12]

Figure 5 plots the cross-sectional average of the regression estimates of equation (7). From the top to bottom, it reports the average intercept α_i, the coefficient of the market

[11] Because there is no established procedure about how to conduct this exercise, we adopt the most straightforward procedure, i.e. regressing the idiosyncratic jump risk against the market jump risk and take the constant with the residual.

[12] Dropping the intercept mainly affects the absolute value of the idiosyncratic jump risk, but does not affect the relative value of the idiosyncratic jump risk across different firms.

jump risk, β_i, the R^2, and the number of observations in each month. From the figure, we can find that the average coefficient in front of the market jump risk ranges around 0, suggesting that the correlation between the market jump risk and the idiosyncratic jump risk is low. The pattern of the average R^2 suggests that the correlation varies across the time. The average R^2 is about 20% and seems decrease in the latter sample period. The average number of observations used in each regression is above 10. In sum, Figure 5 shows the estimation of equation (7) is normal-behaved.

Next, we check whether our method indeed clears impacts from market jump risks. We calculate as the average of the pairwise correlation between the market jump risk and the idiosyncratic jump risk of individual firms. If equation (7) does not purify all systematic shocks, then there should be positive correlations between idiosyncratic jump risks with market jump risks.

The correlations are plotted in Figure 6. It shows that while the correlation between market jump risks with the raw idiosyncratic jump risk is non-zero, the correlation between market jump risks with the adjusted idiosyncratic jump risk is zero. Thus, we conclude that the linear regression removes some of the impacts from the market jump risk.

5.2 The Common Idiosyncratic Jump Risk and the Market Jump Risk

We could also run the following regression to directly check the correlation between the CIJ and the market jump risk:

$$\text{CIJ}_t = \text{Constant} + \beta_{\text{Market Jump}} \times \text{Market Jump}_t + \epsilon_t \tag{8}$$

If the market jump risk has a large impact on CIJ, then $\beta_{\text{Market Jump}}$ should be significant and the adjusted R^2 should be high.

The estimation result is reported in in Table 9. The Pearson correlation coefficients among CIJ, the market jump risk, and the residuals are reported. Table 9 shows $\beta_{\text{Market Jump}}$ is significant, the adjusted R^2 is around 32%. Thus about two-third of the variation in CIJ cannot be explained by the market jump. Moreover, the correlation between the estimated residuals with market jump is zero but highly correlated with the CIJ. Figure 7 plots the time series of CIJ and the residuals of equation (8). It clearly shows the CIJ and the residuals are closely correlated. Given the non-correlation between the residual and the market jump risk, we conclude that CIJ is a common factor that different than the market jump factor.

5.3 The Common Idiosyncratic Jump Risk and the Idiosyncratic Jump Risk of Individual Firms

After calculating CIJ, we run the following regression to test the explanatory power of CIJ on the indiosyncratic jump risk of individual firms:

$$\begin{aligned} &\text{Adj. Idio. Jump}_{i,t} = \text{Constant}_i + \beta_i \times \text{CIJ}_t + \text{Controls} + \epsilon_{i,t} \\ &\text{Idio. Jump}_{i,t} = \text{Constant}_i + \beta_i \times \text{CIJ}_t + \text{Controls} + \epsilon_{i,t} \end{aligned} \tag{9}$$

where Adj. Idio. $\text{Jump}_{i,t}$ is the adjusted idiosyncratic jump risk of firm i at time t, Idio. $\text{Jump}_{i,t}$ denotes the raw idiosyncratic jump risk of firm i at time t, CIJ_t is the common idiosyncratic jump risk at time t. We run the regression for each firm over the entire sample period. We control for the market jump risk in the regression. The average estimated R^2 represents how much of total variations that CIJ could explain.

The regression results are reported in Table 10. We find two findings. First, the average adjusted R^2 in the adjusted idiosyncratic jump regression is approximately 18% (21%) for the monthly regression and is approximately 38% (41%) for the annual regression. It shows that CIJ factor itself explain a significant proportion of the firm's idiosyncratic jump risk. Second, After adding market jumps to the regression, the adjusted R^2 is only approved by 8% (18%) in the monthly (annual) specification. Thus, CIJ has more explanatory power to the idiosyncratic jump of individual firms than the market jump.

5.4 The Common Idiosyncratic Jump Risk and the Cross-Section of Stock Returns

After identifying that CIJ is different from the market jump risk, we study its asset pricing implication. We focus on whether CIJ is a systematic risk factor that affects the cross-section of stock returns.

The empirical procedure is as follows. On each month, we regress the excess return of individual equities on CIJ using the data of past six months, while controlling for the market returns.[13] The regression specification is as follows:

$$\text{Excess Ret}_{i,t} = \text{Constant} + \beta_{\text{MKT},i} \times \text{Market Ret}_t + \beta_{\text{CIJ},i} \times \text{CIJ}_t + \epsilon_{i,t} \tag{10}$$

Then we sort the stocks into five portfolios based on estimated $\beta_{\text{CIJ},i}$ and calculate the equal-weight return on each portfolio. We also report difference of the return on two extreme portfolios and the alphas that after controlling for the Fama-French 3 factor and the Carhart 4 factor.

Table 11 reports the sorting results. It clearly shows a decreasing pattern between the portfolio returns and the β_{CIJ}. This is intuitive because an increment of CIJ means an increase in the average probability of an idiosyncratic jump would occur. Although it would not affect the whole market, it should affect the individual firms. If investors have limits to arbitrage (Shleifer and Vishny (1997)), hold too concentrated portfolios (Benartzi (2001) and Cohen (2009)), or have little protection against the unemployment

[13] We don not control for other factors such as the Fama-French factors when estimating $\beta_{\text{CIJ},i}$. This is to make sure that $\beta_{\text{CIJ},i}$ can be estimated accurately. We do control for the other factors when calculating the alpha. This procedure is consistent with the ones in existing studies. See, for example, Ang, Hodrick, Xing, and Zhang (2006) and Cremers, Halling, and Weinbaum (2015) for more details.

risk (Berk, Stanton, and Zechner (2010) and Lustig, Syverson, and Van Nieuwerburgh (2011)), then the shocks to individual firms would severely impacts the consumption of individuals. Thus investors demand assets with high β_{CIJ} because those assets can hedge against the individual consumption risk. This demand would bid up the asset prices and lower the asset return. Thus the common idiosyncratic jump risk should carry a negative risk premium.

To control for the effect of the market jump risk, we construct double sorted portfolios on β_{CIJ} and $\beta_{\text{Market Jump}}$. The β_{CIJ} and $\beta_{\text{MKT Jump}}$ are calculated from the following regression:

$$\text{Excess Ret}_{i,t} = \text{Constant} + \beta_{\text{MKT},i} \times \text{Market Ret}_t + \beta_{\text{CIJ},i} \times \text{CIJ}_t + \beta_{\text{MKT Jump},i} \times \text{MKT Jump}_t + \epsilon_{i,t} \tag{11}$$

where $\text{Excess Ret}_{i,t}$, Market Ret_t, and CIJ_t have the same definitions as in regression (10). MKT Jump_t has the same definition as in regression (7).

Table 12 reports the alphas after controlling for the Fama-French 3 factors. We find the decreasing pattern persists for certain portfolios, even after controlling for $\beta_{\text{MKT Jump}}$. This results show $\beta_{\text{MKT Jump}}$ cannot fully absorb the impact of β_{CIJ}, suggesting that CIJ is a systematic risk factor that independent of the market jump.

6 Conclusion

We contribute to the literature by using an option-based approach to study the idiosyncratic jump risk of individual firms, which we implement for a large number of firms over a twenty-year period. We find the idiosyncratic jump risk carries a significant negative risk premium and is related to firm characteristics. It also helps to explain part of the idiosyncratic volatility puzzle.

Moreover, we show the existence of a common idiosyncratic jump risk factor that explains a significant portion of the idiosyncratic jump risk of different firms. This common factor is different from the market jump risk and affects the cross-section of stock returns. Sorting exercise verifies that this common factor has a negative risk premium, suggesting that investors would like to pay to hedge both the market jump risk and the common idiosyncratic jump risk.

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Table 1
Summary Statistics of the Selected Options

We report the summary statistics of the options. We report the mean, standard deviation, minimum, and maximum of option returns, price, bid-ask spread, trade volume, open interest, days to maturity, and moneyness. Short-term options are the options that maturing in the nearest month. Long-term options are the ones that maturing in the second nearest month. The data is on daily frequency. The sample period is from January, 1996 to April, 2016.

		Short-Term Call				Short-Term Put			
	N. Obs	Mean	STD	Min	Max	Mean	STD	Min	Max
Option Return	3087639	0.10%	26.92%	-98.66%	1407.14%	-0.78%	25.09%	-97.75%	878.95%
Option Price	3087639	1.99	1.92	0.50	85.56	1.94	1.88	0.50	76.75
Relative Spread	3087639	14.47%	8.87%	0.29%	50.00%	14.95%	9.14%	0.25%	50.00%
Volume	3087639	166.98	748.89	0	90,497	109.74	565.36	0	114965
Open Interest	3087639	1,437.95	4,239.46	1	385,836	944.99	3,063.36	1	231268
Days to Maturity	3087639	35.77	16.72	14	152	35.77	16.72	14	152
Moneyness	3087639	1.00	0.02	0.96	1.04	1.00	0.02	0.96	1.04
		Long-Term Call				Long-Term Put			
	N. Obs	Mean	STD	Min	Max	Mean	STD	Min	Max
Option Return	3087639	0.20%	16.60%	-96.01%	965.00%	-0.32%	14.89%	-94.62%	397.56%
Option Price	3087639	3.25	2.99	0.5	102.25	3.12	2.88	0.50	92.88
Relative Spread	3087639	10.79%	6.48%	0.20%	50.00%	10.98%	6.55%	0.25%	50.00%
Volume	3087639	66.74	425.67	0	118959	43.84767	340.9091	0	98360
Open Interest	3087639	1,185.37	3,983.38	1	395452	777.79	3,009.89	1	252166
Days to Maturity	3087639	93.69	37.70	42	180	93.69	37.70	42	180
Moneyness	3087639	1.00	0.02	0.96	1.04	1.00	0.02	0.96	1.04

Table 2
Distribution of the Options on Five Option Characteristics

We report the the distribution of options on five option characteristics. The characteristics are the moneyness, the maturity, the trading volume, the open interest, and the relative bid-ask spread. For each characteristics, we divide the sample into several bins and report the number of observations and the corresponding percentage for each bin. The data is on daily frequency. The sample period is from January, 1996 to April, 2016.

	Moneyness		
	[0.96,0.98]	(0.98,1.02]	(1.02,1.04]
Short-Term Call / Put			
N. Options	623400	1885300	578939
Percentage	20.19%	61.06%	18.75%
Long-Term Call / Put			
N. Options	628720	1872917	586002
Percentage	20.36%	60.66%	18.98%

	Days to Maturity					
	(0,30]	(30,60]	(60,90]	(90,120]	(120,150]	(150,180]
Short-Term Call / Put						
N. Options	1305602	1528316	231882	15743	5869	227
Percentage	42.28%	49.50%	7.51%	0.51%	0.19%	0.01%
Long-Term Call /Put						
N. Options	0	888329	651150	646078	625696	276386
Percentage	0%	28.77%	21.09%	20.92%	20.26%	8.95%

	Volume					
	0	(0,100]	(100,500]	(500,1000]	(1000,1500]	(1500, Max]
Short-Term Call						
N. Options	989614	1429461	450761	104250	43594	69959
Percentage	32.05%	46.30%	14.60%	3.38%	1.41%	2.27%
Short-Term Put						
N. Options	1396571	1221449	324219	71092	30058	44250
Percentage	45.23%	39.56%	10.50%	2.30%	0.97%	1.43%
Long-Term Call						
N. Options	1443728	1321434	242167	42082	16187	22041
Percentage	46.76%	42.80%	7.84%	1.36%	0.52%	0.71%
Long-Term Put						
N. Options	1882347	995121	159125	26070	10637	14339
Percentage	60.96%	32.23%	5.15%	0.84%	0.34%	0.46%

	Open Interest					
	(0,1]	(1,100]	(100,500]	(500,1000]	(1000,1500]	(1500,]
Short-Term Call						
N. Options	16571	811686	977439	421512	219236	641195
Percentage	0.54%	26.29%	31.66%	13.65%	7.10%	20.77%
Short-Term Put						
N. Options	28945	1185153	938567	336759	167679	430536
Percentage	0.94%	38.38%	30.40%	10.91%	5.43%	13.94%
Long-Term Call						
N. Options	21435	965048	1015206	391696	188130	506124
Percentage	0.69%	31.26%	32.88%	12.69%	6.09%	16.39%
Long-Term Put						
N. Options	36925	1348194	944024	297953	134919	325624
Percentage	1.20%	43.66%	30.57%	9.65%	4.37%	10.55%
	Relative Bid-Ask Spread					
	(0,0.05]	(0.05, 0.1]	(0.1,0.2]	(0.2,0.3]	(0.3,0.4]	(0.4,0.5]
Short-Term Call						
N. Options	289375	839813	1283229	461468	168036	45718
Percentage	9.37%	27.20%	41.56%	14.95%	5.44%	1.48%
Short-Term Put						
N. Options	271169	806079	1276123	490635	191032	52601
Percentage	8.78%	26.11%	41.33%	15.89%	6.19%	1.70%
Long-Term Call						
N. Options	481106	1199339	1145840	208019	43596	9739
Percentage	15.58%	38.84%	37.11%	6.74%	1.41%	0.32%
Long-Term Put						
N. Options	472240	1156739	1181449	223907	43863	9441
Percentage	15.29%	37.46%	38.26%	7.25%	1.42%	0.31%

Table 3
Summary Statistics of the Return of the Idiosyncratic Jump Portfolio

We report the summary statistics of the return on the idiosyncratic jump option portfolio. The idiosyncratic jump option portfolio is a Delta-neutral, Vega-neutral, and Gamma-positive option portfolio that constructed with ATM equity options. We report the statistics in each year as well as in the entire sample period. The sample period is from January, 1996 to April, 2016.

Year	N. Firms	N. Obs	Mean	Std	Min	Median	Max	Skewness	Kurtosis
1996	1185	98365	-0.43%	6.11%	-48.57%	-0.81%	241.21%	3.37	61.46
1997	1472	124157	-0.45%	6.00%	-46.47%	-0.85%	167.67%	2.50	28.68
1998	1613	128723	-0.28%	6.23%	-43.93%	-0.78%	155.01%	2.82	29.87
1999	1718	130070	-0.49%	5.69%	-62.80%	-0.87%	179.16%	2.80	34.18
2000	1619	125690	-0.20%	5.97%	-47.41%	-0.76%	248.82%	3.93	65.43
2001	1516	116066	-0.62%	5.02%	-38.56%	-0.98%	95.69%	2.70	25.14
2002	1485	116101	-0.43%	5.08%	-40.58%	-0.82%	333.63%	5.67	199.31
2003	1425	123425	-0.65%	4.84%	-35.98%	-0.92%	234.62%	3.99	85.45
2004	1561	148615	-0.57%	4.91%	-42.51%	-0.86%	259.58%	4.36	97.69
2005	1595	156685	-0.55%	5.07%	-45.71%	-0.87%	182.30%	3.93	67.35
2006	1678	181102	-0.49%	4.93%	-50.83%	-0.84%	195.72%	3.74	67.11
2007	1777	197787	-0.35%	5.41%	-44.77%	-0.81%	168.03%	3.01	37.27
2008	1723	171628	0.05%	5.81%	-46.69%	-0.64%	279.67%	3.20	53.67
2009	1598	152272	-0.57%	4.68%	-39.27%	-0.96%	122.03%	2.68	32.26
2010	1642	161047	-0.46%	5.01%	-54.86%	-0.87%	237.81%	3.34	70.22
2011	1579	154915	-0.21%	5.75%	-42.34%	-0.83%	159.11%	3.15	32.01
2012	1474	144386	-0.51%	5.07%	-44.56%	-0.87%	166.16%	3.22	49.96
2013	1701	171879	-0.44%	4.98%	-47.96%	-0.82%	181.28%	3.75	69.90
2014	1805	206120	-0.36%	4.94%	-45.32%	-0.75%	254.84%	3.69	79.49
2015	1855	216245	-0.29%	5.14%	-42.31%	-0.73%	186.81%	2.95	45.09
2016	1519	62361	-0.15%	4.97%	-37.44%	-0.59%	109.62%	2.44	29.46
1996 - 2016	4993	3087639	-0.40%	5.31%	-62.80%	-0.82%	333.63%	3.39	57.61

Table 4
The Idiosyncratic Jump Risk in Sub-Samples

We report the summary statistics of the idiosyncratic jump risk in two sub-samples. The first sub-sample contains all the days when the return on the underlying stock is positive. The second contains the days when the return on the underlying stock is negative. We calculate average idiosyncratic jump risk in both samples to see how it relates to the direction of the underlying price movement. The sample period is from January, 1996 to April, 2016.

Return on the Underlying is Positive				Return on the Underlying is Negative			
Year	N.Obs	Mean	Std	Year	N.Obs	Mean	Std
1996	43657	-0.45%	6.08%	1996	45460	-0.36%	6.26%
1997	57387	-0.45%	6.02%	1997	58449	-0.40%	6.02%
1998	60238	-0.39%	6.11%	1998	62776	-0.12%	6.39%
1999	59661	-0.52%	5.86%	1999	64916	-0.43%	5.57%
2000	59076	-0.31%	5.98%	2000	62594	-0.07%	5.96%
2001	56671	-0.71%	4.80%	2001	57850	-0.52%	5.23%
2002	55422	-0.47%	5.18%	2002	59629	-0.37%	4.99%
2003	63119	-0.54%	4.94%	2003	58842	-0.77%	4.73%
2004	74764	-0.57%	5.00%	2004	72174	-0.56%	4.84%
2005	77867	-0.57%	5.07%	2005	77042	-0.53%	5.06%
2006	90638	-0.39%	5.05%	2006	88628	-0.59%	4.81%
2007	99539	-0.34%	5.44%	2007	96518	-0.35%	5.39%
2008	82662	0.07%	5.71%	2008	87861	0.05%	5.91%
2009	79126	-0.49%	4.79%	2009	71863	-0.65%	4.55%
2010	82236	-0.47%	4.94%	2010	77310	-0.44%	5.09%
2011	77653	-0.23%	5.74%	2011	76148	-0.19%	5.76%
2012	72003	-0.43%	5.11%	2012	71051	-0.60%	5.02%
2013	90411	-0.44%	4.90%	2013	79885	-0.44%	5.06%
2014	105832	-0.44%	4.94%	2014	98563	-0.27%	4.96%
2015	107702	-0.34%	5.02%	2015	107003	-0.23%	5.26%
2016	32927	-0.18%	5.05%	2016	29089	-0.11%	4.87%
1996-2016	1528591	-0.41%	5.29%	1996-2016	1503651	-0.38%	5.33%

Table 5
The Cross-Sectional Relationship Between the Idiosyncratic Jump Risk and the Firm Characteristics

We report the cross-sectional relationship between the idiosyncratic jump risk and the firm characteristics. Panel A reports the contemporaneous relationship and Panel B reports the out-of-sample relationship. The sample period is from January, 1996 to April, 2016.

	Contemporaneous Relationship									
	1	2	3	4	5	6	7	8	9	10
Stock Return	-0.14%	-0.45%	-0.52%	-0.53%	-0.54%	-0.53%	-0.47%	-0.41%	-0.27%	0.02%
Stock Price	-0.59%	-0.46%	-0.46%	-0.41%	-0.32%	-0.32%	-0.33%	-0.34%	-0.32%	-0.29%
Stock Dollar Volume	-0.77%	-0.65%	-0.56%	-0.46%	-0.43%	-0.36%	-0.27%	-0.21%	-0.13%	-0.01%
Realized Vol	-0.94%	-0.72%	-0.61%	-0.51%	-0.43%	-0.38%	-0.32%	-0.21%	-0.04%	0.31%
Realized Skew	-0.21%	-0.45%	-0.46%	-0.47%	-0.46%	-0.45%	-0.43%	-0.40%	-0.35%	-0.17%
Realized Kurt	-0.46%	-0.49%	-0.47%	-0.45%	-0.44%	-0.43%	-0.42%	-0.34%	-0.23%	-0.11%
Industry	-0.46%	-0.37%	-0.35%	-0.29%	-0.35%	-0.35%	-0.38%	-0.58%	-0.40%	-0.39%
Market Size	-0.64%	-0.53%	-0.46%	-0.42%	-0.38%	-0.38%	-0.36%	-0.30%	-0.23%	-0.14%
Idio. Vol	-0.79%	-0.67%	-0.58%	-0.50%	-0.46%	-0.39%	-0.35%	-0.22%	-0.11%	0.25%
Stock Illiquidity	-0.22%	-0.25%	-0.28%	-0.31%	-0.37%	-0.38%	-0.43%	-0.45%	-0.52%	-0.63%
	Out-of-Sample Relationship									
	1	2	3	4	5	6	7	8	9	10
Stock Return	-0.43%	-0.40%	-0.38%	-0.38%	-0.38%	-0.41%	-0.35%	-0.38%	-0.37%	-0.40%
Stock Price	-0.60%	-0.44%	-0.43%	-0.43%	-0.34%	-0.34%	-0.35%	-0.31%	-0.33%	-0.29%
Stock Dollar Volume	-0.63%	-0.58%	-0.51%	-0.46%	-0.40%	-0.37%	-0.31%	-0.26%	-0.21%	-0.12%
Realized Vol	-0.44%	-0.40%	-0.39%	-0.36%	-0.38%	-0.37%	-0.35%	-0.36%	-0.36%	-0.46%
Realized Skew	-0.50%	-0.38%	-0.36%	-0.36%	-0.34%	-0.34%	-0.37%	-0.35%	-0.38%	-0.49%
Realized Kurt	-0.33%	-0.33%	-0.34%	-0.34%	-0.34%	-0.36%	-0.37%	-0.43%	-0.45%	-0.56%
Industry	-0.46%	-0.37%	-0.35%	-0.29%	-0.35%	-0.35%	-0.38%	-0.58%	-0.40%	-0.39%
Market Size	-0.61%	-0.56%	-0.46%	-0.41%	-0.40%	-0.38%	-0.34%	-0.31%	-0.24%	-0.14%
Idio. Vol	-0.41%	-0.37%	-0.36%	-0.37%	-0.39%	-0.34%	-0.36%	-0.37%	-0.40%	-0.50%
Stock Illiquidity	-0.16%	-0.22%	-0.29%	-0.33%	-0.38%	-0.36%	-0.46%	-0.47%	-0.56%	-0.63%

Table 6
Fama-MacBeth Regression of Idiosyncratic Jump Risks and the Firm Characteristics

We report the results of a Fama-MacBeth type of regression where the idiosyncratic jump risk is regressed against the firm size, idiosyncratic volatility, and stock illiquidity. The results of both univariate and multivariate regression are reported. In the multivariate regression, we control for the share price of last month, the average bid-ask spread, the realized skewness, coskewness, the upside beta, and the downside beta. Standard errors are adjusted by Newey-West (1987) method with lag of one period. T-statistics are reported in the parenthesis. The sample period is from January, 1996 to April, 2016.

	Idio. Jump	Idio. Jump	Idio. Jump	Idio. Jump	Idio. Jump
Market Size	0.0008***			0.0007***	0.0002**
	(9.7074)			(9.0620)	(2.5039)
Idio. Vol		-0.0006***		-0.0002**	-0.0015***
		(-5.4718)		(-2.3484)	(-4.2155)
Stock Illiquidity			-0.0020***	-0.0016***	-0.0015***
			(-9.1970)	(-8.0162)	(-7.4947)
Constant	-0.0038***	-0.0040***	-0.0040***	-0.0041***	-0.0038***
	(-12.3900)	(-12.7860)	(-12.8770)	(-13.0730)	(-10.6880)
Controls	No	No	No	No	Yes
Adj. R^2	0.0014	0.0022	0.0034	0.0060	0.0122
N.Obs	278511	278511	278511	278511	278490

Table 7
Returns of the Value-Weighted Portfolios that are Single-Sorted on Idiosyncratic Jumps

We report the average return, CAPM alpha, Fama-French 3-factor alpha, and Carhart 4-factor alpha of the portfolios that are sorted on the magnitude of the idiosyncratic jump risk. In each month, we sort stocks into five portfolios based on the average return on their idiosyncratic jump option portfolio. Then we calculate the realized average daily return in the next month. Portfolio 1 has the lowest idiosyncratic jump risk and Portfolio 5 has the highest idiosyncratic jump risk. The numbers are in percentages. Standard errors are adjusted by Newey-West (1987) method with lag of one period. T-statistics are reported in the parenthesis. The sample period is from January, 1996 to April, 2016.

	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha
1	1.0035	0.3761	0.3512	0.2940
Low IJump	(3.0135)	(2.2142)	(2.2825)	(1.8932)
2	0.8439	0.1358	0.1634	0.1329
	(2.8227)	(1.1741)	(1.4737)	(1.0977)
3	0.7412	0.0449	0.0852	0.0088
	(2.3747)	(0.3918)	(0.8509)	(0.0920)
4	0.7821	0.0298	0.0669	0.0562
	(2.5450)	(0.3015)	(0.6545)	(0.5542)
5	0.4259	-0.3805	-0.3668	-0.3054
High IJump	(1.1591)	(-3.0807)	(-2.8813)	(-2.2334)
High - Low	-0.5776***	-0.7566***	-0.7180***	-0.5993**
	(-2.7479)	(-3.2302)	(-3.1941)	(-2.4892)

Table 8

Returns of the Value-Weighted Portfolios that are Double-Sorted on the Idiosyncratic Jump Risk and the Idiosyncratic Volatility Risk

We report the Fama-French 3-factor alpha of double-sorted portfolios that are based on the idiosyncratic jump risk and idiosyncratic volatility risk. In each month, we calculate the average return on the idiosyncratic jump portfolio and the realized idiosyncratic volatility. We first form five quintile groups based on the average return on the idiosyncratic jump portfolio. Then we further form five groups based on the realized idiosyncratic volatility for each quintile group. We calculate the value-weighted average returns for each of the 25 portfolios. The Fama-French 3-factor alpha is the intercept of regressing the portfolio return on the Fama-French 3 factors. The numbers are in percentages. Standard errors are adjusted by Newey-West (1987) method with lag of one period. T-statistics are reported in the parenthesis. The sample period is from January, 1996 to April, 2016.

	Low IVol				High IVol	
FF3 Alpha	1	2	3	4	5	High - Low
1	0.3084	0.4596	0.0114	0.1711	-0.0418	-0.3502
Low IJump	(1.5093)	(2.0613)	(0.0500)	(0.5203)	(-0.1040)	(-0.8212)
2	0.3773	0.1133	0.2899	0.0235	-0.4315	-0.8088*
	(2.2514)	(0.5960)	(1.0488)	(0.0861)	(-1.2314)	(-1.9215)
3	0.2691	-0.1265	0.1518	-0.0314	-0.6930	-0.9621***
	(1.6354)	(-0.6756)	(0.6802)	(-0.1370)	(-2.1831)	(-2.6157)
4	0.1514	0.1941	0.0979	-0.2969	-0.2374	-0.3888
	(0.8125)	(1.1495)	(0.4816)	(-0.9818)	(-0.5785)	(-0.8511)
5	-0.3889	-0.1071	-0.1537	-0.6622	-1.0745	-0.6856
High IJump	(-1.9027)	(-0.5022)	(-0.6612)	(-1.6916)	(-2.4930)	(-1.3756)
High - Low	-0.6972***	-0.5668*	-0.1651	-0.8333	-1.0327*	-0.3355
	(-2.6228)	(-1.7488)	(-0.5190)	(-1.4855)	(-1.7178)	(-0.5552)

Table 9
The Relationship Between the Common Idiosyncratic Jump Risk and the Market Jump Risk

We report the estimation results of following regressions.

$$\text{CIJ}_t = \text{Constant} + \beta_{\text{Market Jump}} \times \text{Market Jump}_t + \epsilon_t$$

where CIJ_t denotes the common idiosyncratic jump risk at time t and Market Jump_t denotes the market jump risk at time t. The regressions are conducted using monthly observations. Panel A reports the regression estimates. Panel B reports the correlation between the common idiosyncratic jump risk, the market jump risk, and the residual of the above regression. The sample period is from January, 1996 to April, 2016.

Panel A: Regression Estimates

	Constant	$\beta_{\text{Market Jump}}$	Adjusted R^2	N. Obs
Estimated Coefficients	-0.0009	0.3032	0.3272	236
T-Stats	(-3.71)	(48.86)		

Panel B: Correlation Matrix

	CIJ_t	Market Jump_t	ϵ_t
CIJ_t	1		
Market Jump_t	0.5722	1	
ϵ_t	0.8201	0.0000	1

Table 10
The Explanatory Power of CIJ

We report the results about the explanatory power of CIJ on the idiosyncratic jump risk of individual firms. The explanatory regression is specified as follow.

$$\text{Adj. Idio. Jump}_{i,t} = \text{Constant}_i + \beta_i \times \text{CIJ}_t + \text{Controls} + \epsilon_{i,t}$$
$$\text{Idio. Jump}_{i,t} = \text{Constant}_i + \beta_i \times \text{CIJ}_t + \text{Controls} + \epsilon_{i,t}$$

where Adj. Idio. $\text{Jump}_{i,t}$ denotes the adjusted idiosyncratic jump risk of stock i at time t and Idio. $\text{Jump}_{i,t}$ denotes the return on the idiosyncratic jump risk portfolio of stock i at time t. Adj. Idio. $\text{Jump}_{i,t}$ is defined in equation (7). The regressions are conducted for every stock in every month (year). Panel A reports the monthly regression results and panel B reports the annual regression results. The cross-sectional average of the estimates are reported. The control variable is the market jump risk. The sample period is from January, 1996 to April, 2016.

Panel A: Monthly Regressions

	Adj. Idio. Jump	Adj. Idio. Jump	Idio. Jump	Idio. Jump
Average Constant	-0.0090	-0.0022	-0.0023	-0.0027
Average β	-0.9118	0.4676	0.7556	0.3479
Average R^2	0.1802	0.2625	0.2101	0.2911
Average N.Obs	823	822	823	822
With Market Jumps?	No	Yes	No	Yes

Panel B: Annual Regressions

	Adj. Idio. Jump	Adj. Idio. Jump	Idio. Jump	Idio. Jump
Average Constant	-0.0145	-0.0086	-0.0025	-0.0030
Average β	-1.9549	-0.9712	0.6951	1.0068
Average R^2	0.3890	0.5779	0.4144	0.5991
Average N.Obs	7	6	7	6
With Market Jumps?	No	Yes	No	Yes

Table 11
Returns of Value-Weighted Portfolios that are Single-Sorted on β_{CIJ}

We report the average return, CAPM alpha, Fama-French 3-factor alpha, and Carhart 4-factor alpha of the stock portfolios sorted on β_{CIJ}. In each month, we sort stocks into five portfolios based on the estimated β_{CIJ}, where β_{CIJ} are estimated using the returns of the past six months. Then we calculate the value-weighted return for each portfolio in the next month. Portfolio 1 has the lowest β_{CIJ} and Portfolio 5 has the highest β_{CIJ}. The numbers are in percentages. Standard errors are adjusted by Newey-West (1987) method with lag of six periods. T-statistics are reported in the parenthesis. The sample period is from January, 1996 to April, 2016.

	Average Return	CAPM Alpha	FF3 Alpha	Carhart4 Alpha
1	0.0516	0.0086	0.0105	0.0068
Low β_{CIJ}	(2.1883)	(0.7552)	(1.0018)	(0.6320)
2	0.0419	0.0055	0.0059	0.0020
	(2.4701)	(1.1936)	(1.2846)	(0.4449)
3	0.0450	0.0098	0.0100	0.0084
	(2.9218)	(2.8367)	(3.0391)	(2.4629)
4	0.0390	0.0019	0.0015	0.0041
	(2.2854)	(0.4446)	(0.3452)	(0.9236)
5	0.0287	(0.0169)	(0.0215)	(0.0071)
High β_{CIJ}	(1.1815)	(-1.5314)	(-2.0504)	(-0.7186)
High - Low	-0.0229	-0.0256	-0.0321*	-0.0139
	(-1.3308)	(-1.4910)	(-1.8998)	(-0.8360)

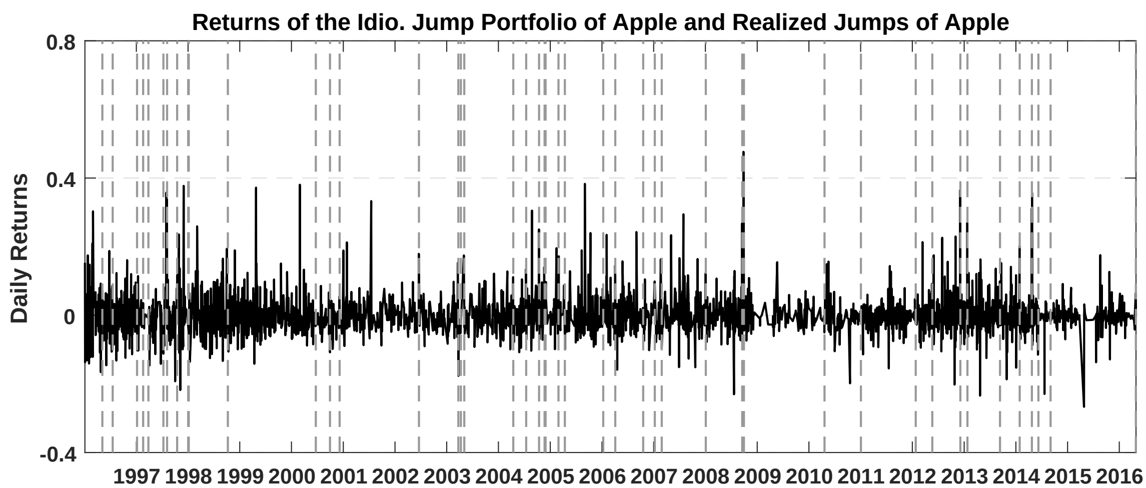
Table 12
Returns of Value-Weighted Portfolios that are Double-Sorted on β_{CIJ} and $\beta_{\text{Market Jump}}$

We report the Fama-French 3-factor alpha of double-sorted portfolios on β_{CIJ} and $\beta_{\text{MKT Jump}}$. In each month, we estimate β_{CIJ} and $\beta_{\text{MKT Jump}}$ using the daily returns of past six months. We first form five quintile portfolios based on β_{CIJ}. Then for each portfolio, we form another five groups based on $\beta_{\text{MKT Jump}}$. We calculate the value-weighted return in the next month for each of the 25 portfolios. The numbers are in percentages. Standard errors are adjusted by Newey-West (1987) method with lag of six periods. T-statistics are reported in the parenthesis. The sample period is from January, 1996 to April, 2016.

	Low $\beta_{\text{MKT Jump}}$				High $\beta_{\text{MKT Jump}}$	
FF3 Alpha	1	2	3	4	5	High - Low
1	-0.0162	0.0252	0.0148	0.0208	-0.0077	0.0085
Low β_{CIJ}	(-0.8282)	(1.6477)	(1.1766)	(1.6165)	(-0.4921)	(0.3875)
2	0.0067	0.0136	-0.0069	0.0025	0.0058	-0.0009
	(0.5648)	(1.5248)	(-0.9302)	(0.3572)	(0.5323)	(-0.0563)
3	-0.0075	0.0125	0.0055	0.0168	0.0063	0.0138
	(-0.7030)	(1.8296)	(0.9645)	(2.5603)	(0.6955)	(0.8959)
4	0.0037	-0.0065	0.0071	0.008	0.0006	-0.0031
	(0.3499)	(-0.8197)	(1.0236)	(1.1052)	(0.0550)	(-0.1940)
5	-0.0165	-0.0098	-0.0147	-0.0275	-0.0042	0.0122
High β_{CIJ}	(-0.9135)	(-0.8093)	(-1.2860)	(-2.0506)	(-0.2419)	-0.5569
High - Low	-0.0003	-0.0350*	-0.0295	-0.0483**	0.0035	
	(-0.0114)	(-1.6730)	(-1.5049)	(-2.4144)	(0.1562)	

Figure 1
Daily Returns of the Idiosyncratic Jump Portfolio of Apple

We plot daily returns of the idiosyncratic jump portfolio of Apple. Vertical dashed lines in the top panel represent realized jumps of Apple stocks. Vertical dashed lines in the bottom panel represent realized jumps of S&P 500. Realized jumps are detected by using the Lee and Mykland (2008) method with daily data. The sample period is from January, 1996 to April, 2016.



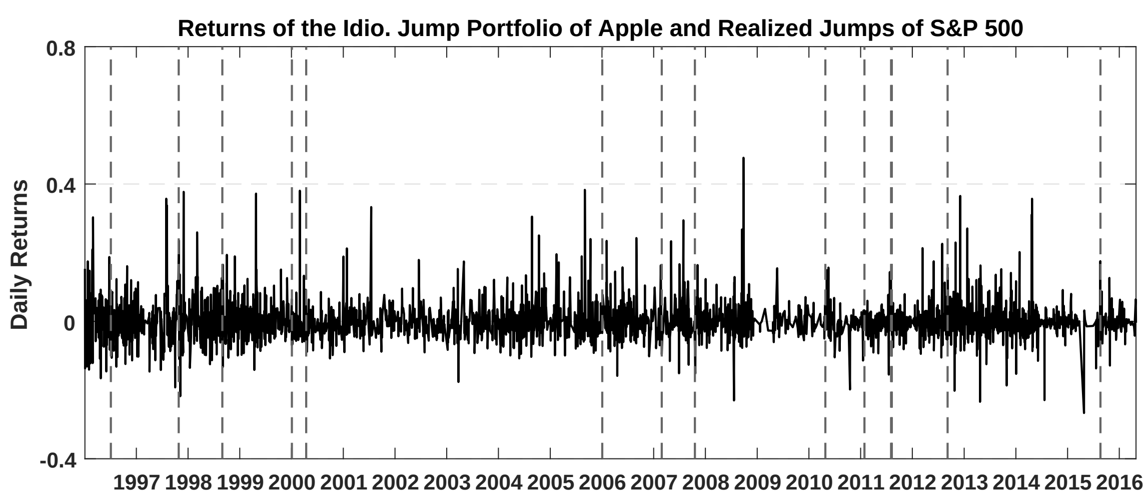


Figure 2
Average Return of the Idiosyncratic Jump Portfolio

We plot the monthly average idiosyncratic jump risk premiums of portfolios sorted on the market size (the top panel), the idiosyncratic volatility (the middle panel), and Amihud illiquidity (the bottom panel). Each panel plots the return on portfolios on two extreme ends. The sample period is from January, 1996 to April, 2016.

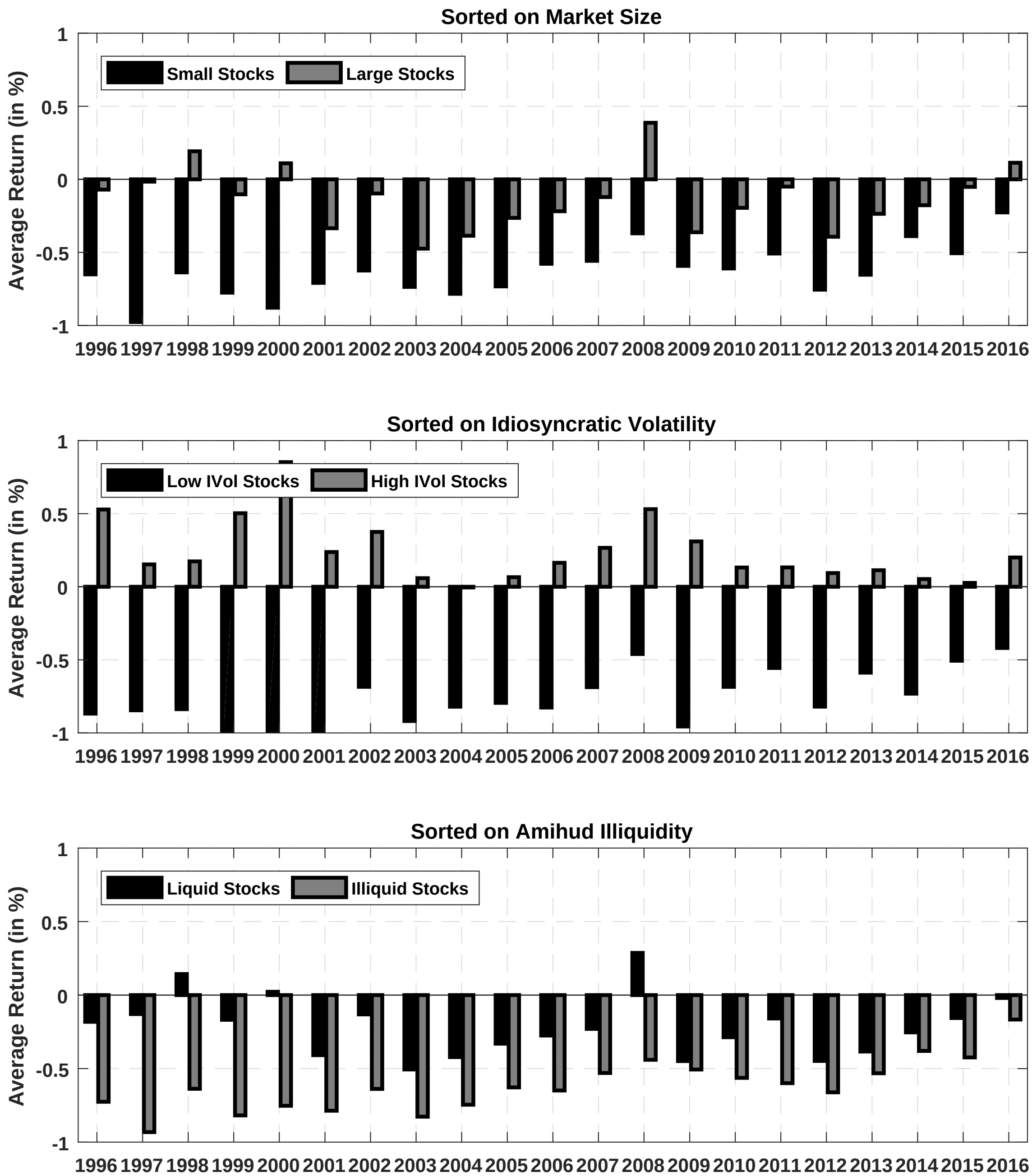


Figure 3
Cumulative Return of the Idiosyncratic Jump Portfolio

We plot the cumulative return on the idiosyncratic jump risk portfolio that are sorted on size (the top panel), the idiosyncratic volatility (the middle panel), and Amihud Illiquidity (the bottom panel). Each panel plots the return on portfolios on two extreme ends. The sample period is from January, 1996 to April, 2016.

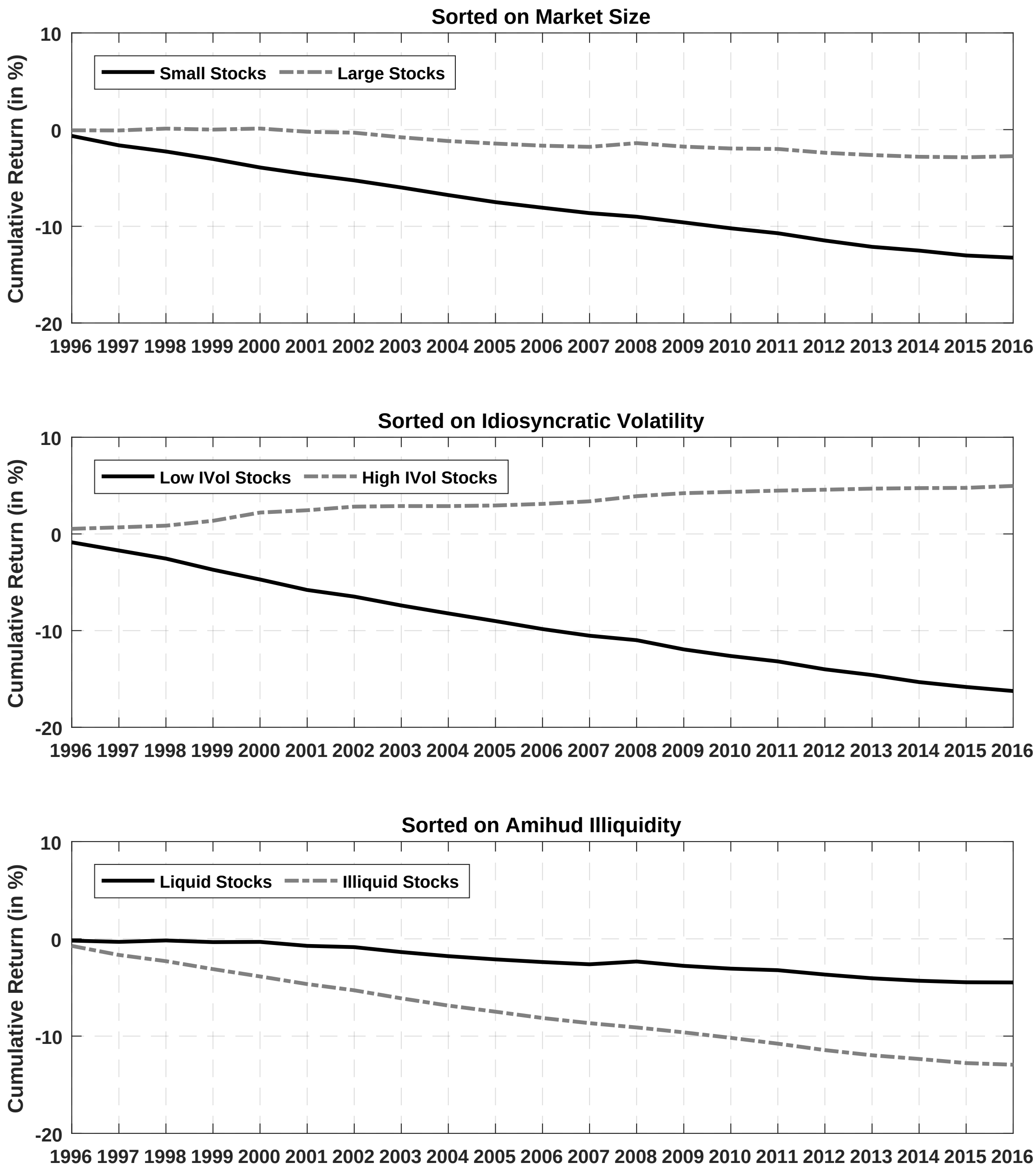
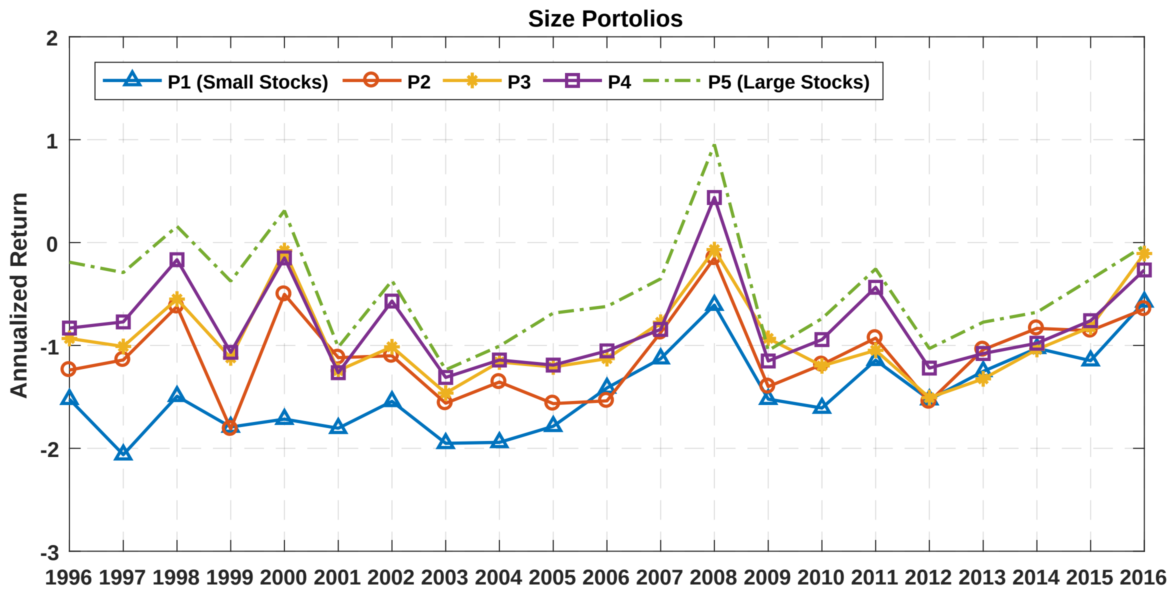


Figure 4
Commonality of Idiosyncratic Jump Risks

We plot the monthly average idiosyncratic jump risks of 5 portfolios that sorted by the market size (the top panel) and the industry code (the bottom panel). The industry code is based on Fama and French's 5 industry portfolio. The sample period is from January, 1996 to April, 2016.



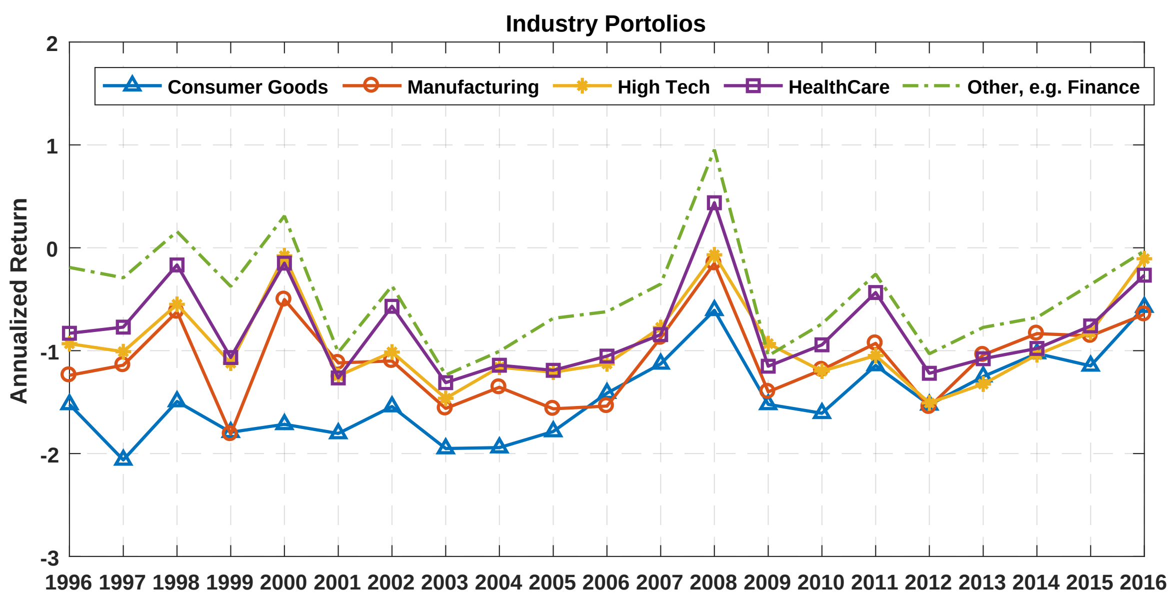


Figure 5
Regressing Idiosyncratic Jump Risks on Market Jump Risks

We plot the estimation result of regressing the idiosyncratic jump risk on the market jump risk. For each stock i and in each month, we run the following regression.

$$\text{Idio. Jump Risk}_{i,t} = \text{Intercept}_i + \text{Slope}_i \times \text{Market Jump Risk}_t + \epsilon_{i,t}$$

Then we take the average of the estimates across all stocks. From the top to bottom, the panel plots the cross-sectional average intercept., the average slope, the average R^2, and the average number of observations respectively. The sample period is from January, 1996 to April, 2016.

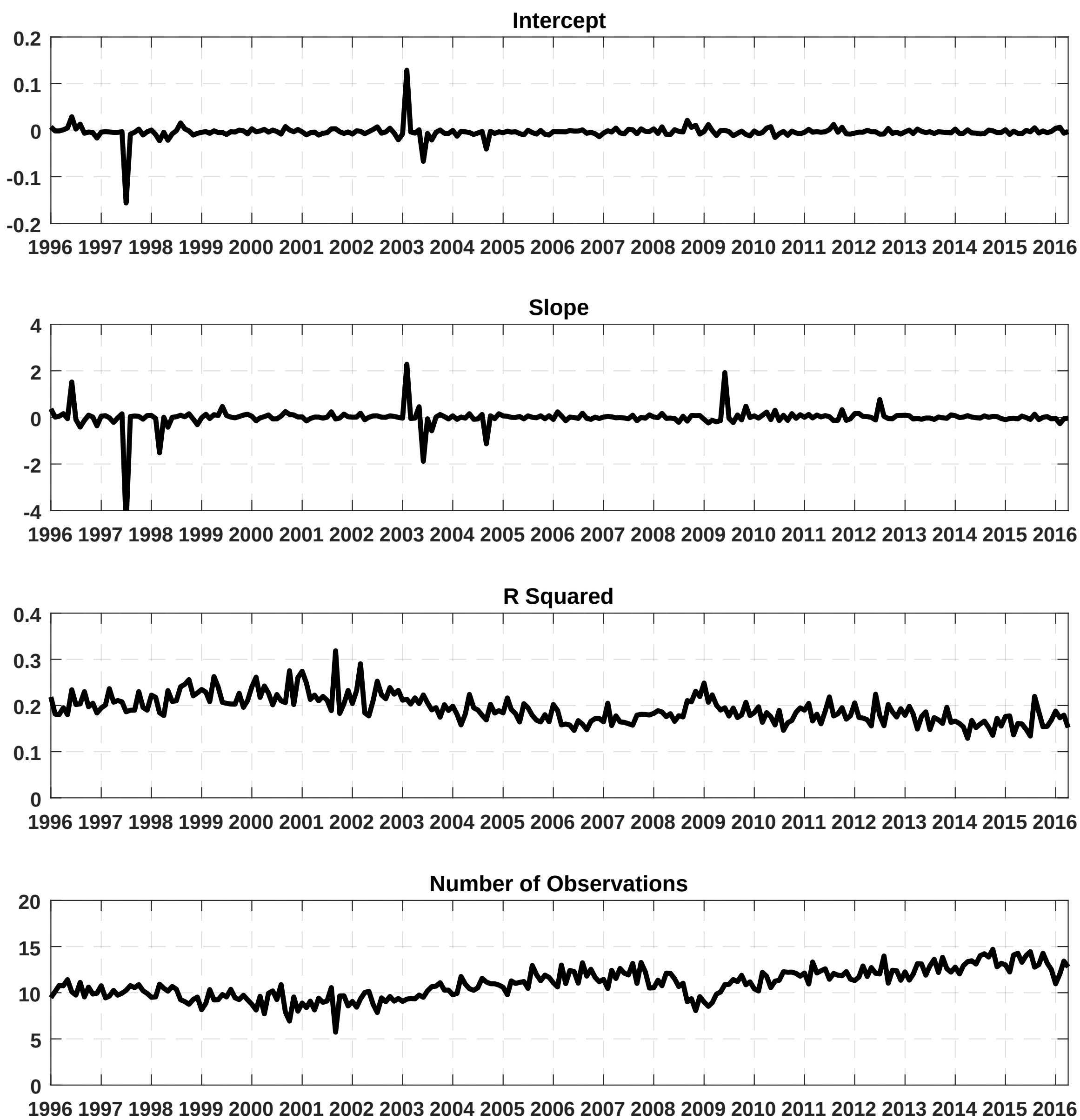


Figure 6
Correlation between the Adjusted Idio. Jump Risk and Market Jump Risk

We plot the correlation between the idiosyncratic jump risk and the market jump risk and the adjusted idiosyncratic jump risk and the market jump risk. The adjusted idiosyncratic jump risk is defined as in equation (7). The sample period is from January, 1996 to April, 2016.

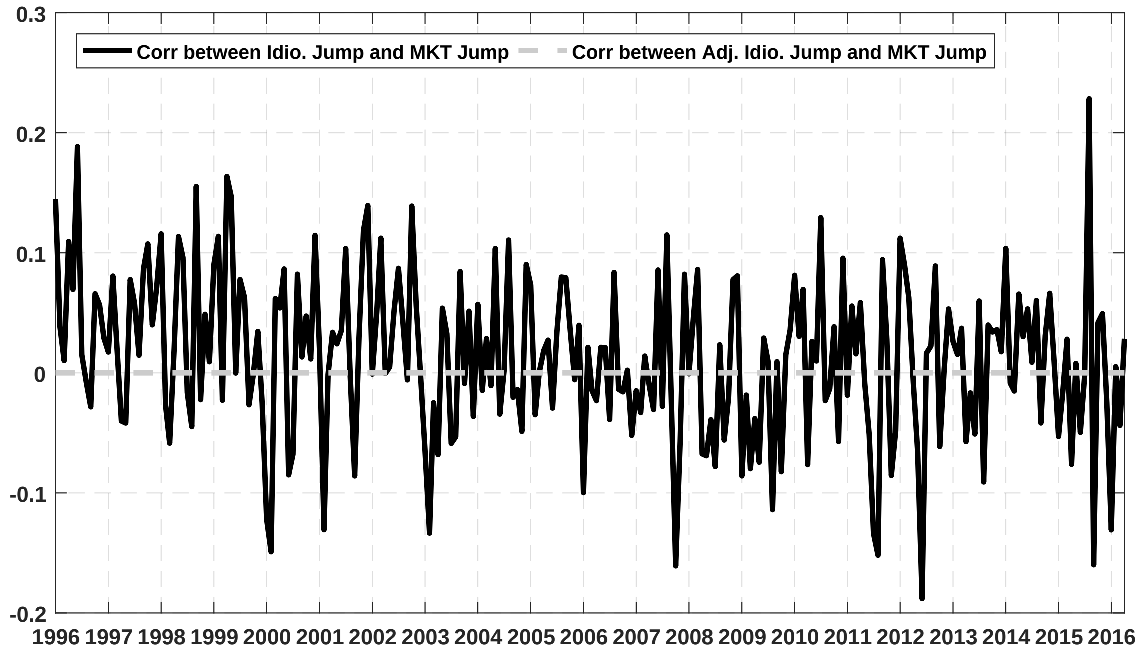
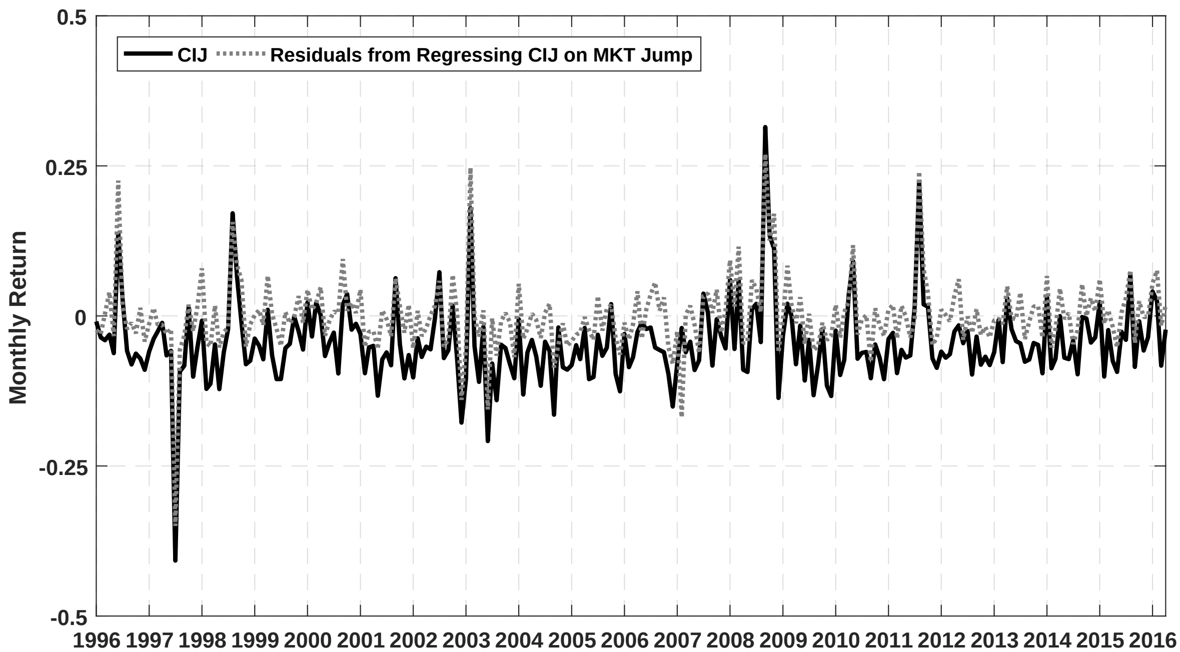


Figure 7
The Common Idiosyncratic Jump Risk

We plot the common idiosyncratic jump risk (the solid line) and the residuals from regressing CIJ on the market jump risk (the dashed line). The sample period is from January, 1996 to April, 2016.



Appendix

A.1 Lee and Mykland (2008) Non-Parametric Method

Following Lee and Mykland (2008), we calculate the statistics $L(i)$ as follows.

$$L(i) = \frac{\log S(t_i)/S(t_{i-1})}{\hat{\sigma}(t_i)} \tag{A.1}$$

where

$$\hat{\sigma}(t_i) = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |\log S(t_j)/S(t_{j-1})| \log S(t_{j-1})/S(t_{j-2})| \tag{A.2}$$

$S(t_i)$ is the stock price at time t_i and K is the length of the rolling window. Because we use daily observations, we let $K = 16$ as suggested by the original paper. The threshold for $\frac{|L(i)-C_n|}{S_n}$ is β, where

$$C_n = \frac{(2\log n)^{0.5}}{c} - \frac{\log \pi + \log(\log n)}{2c(2\log n)^{0.5}} \tag{A.3}$$

and

$$S_n = \frac{1}{c(2\log n)^{0.5}} \tag{A.4}$$

.

n is the number of observations, $\beta = -\log(-\log(1 - \text{Significance Level}))$.

A.2 Idiosyncratic Volatility

Following Ang, Hodrick, Xing, and Zhang (2006), we run the following estimation and define the idiosyncratic volatility as the standard deviation of the residuals.

$$\text{Excess Ret}_{i,t} = \alpha_i + \beta_{MKT,i}\text{MKT}_t + \beta_{SMB,i}\text{SMB}_t + +\beta_{HML,i}\text{HML}_t + \epsilon_{i,t} \tag{A.5}$$

where Excess $\text{Ret}_{i,t}$ is the excess return on stock i at time t, MKT_t is the return on the market portfolio, SMB_t is the return on the small minus big portfolio, and the HML_t is the return on the high minus low portfolio. Those three portfolios are downloaded from French's website. The regression is conducted for each stocks on each month, using all daily observations in that month.

A.3 Amihud (2002) Illiuqidity

The Amihud illiquidity measure is proposed by Amihud (2002). It measures how the trade volume affects price changes. The intuition is that a large amount of trading should have more impacts on the prices of an illiquid asset than the price of a liquid asset. We calculate the Amihud measure as follows.

$$\text{Amihud Illiquidity}_{i,t} = \frac{|\text{Daily Return}_{i,t}|}{\text{Daily Traded Volume}_{i,t}}, \quad i = 1, 2, ..., N \tag{A.6}$$

where Daily $\text{Return}_{i,t}$ is the daily return on stock i at time t and Daily Traded $\text{Volume}_{i,t}$ is the daily total traded volume.