Stock Price Jumps and Cross-Sectional Return Predictability

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Abstract

In rational continuous-time asset pricing models, compensation for risk is represented by the continuous drift of asset prices, whereas jumps are the effect of large information or liquidity shocks. We use this distinction to evaluate risk based explanations of cross-sectional stock return predictability. Based on the CRSP data from 1927 to 2005, we find that individual stock price jumps tend to be idiosyncratic and predominantly positive, presenting an interesting contrast to mostly negative jumps in market portfolios. More importantly, several well-known patterns of return predictability, including the size effect, the liquidity premium, and to a moderate extent the value premium, are the result of cross-sectional differences in stock price jumps. The evidence presents a challenge to theories that attribute such return predictability to simple differences in risk premium. We further explore several alternative hypotheses within the rational asset pricing paradigm, such as the martingale restriction on jumps, jump risk premium effect, investor preference for skewness, and discontinuity in expected returns. However, none of them can be reconciled with the empirical evidence.

Discontinuities are, of necessity, a surprise.
— Alan Greenspan[1]

I. Introduction

Since the seminal work of Merton (1976), a number of studies have shown that jumps in asset prices have significant implications for derivative pricing, risk management, and portfolio allocation.[2] In particular, the empirical literature on jumps has substantially improved our understanding of return properties of various financial assets, such as interest rates, exchange rates, and equity market indexes. However, so far relatively little work has focused on jumps in individual stock prices. In this paper, we fill in the gap by performing a systematic study of price jumps for a large cross-section of individual stocks.

The purpose of our study is twofold. First, we document properties of individual stock price jumps. Second and more importantly, we investigate the role of jumps in explaining cross-sectional stock return predictability. Our analysis is based on a key distinction between the jump component and the risk premium of stock returns. Jumps in stock prices – large discontinuous price movements – are due to infrequent and large surprises to investor's information set (or liquidity). On the other hand, because investors have risk exposure continuously (which may also include jump risk), compensation for risk is required on a continuous basis and, in the continuous-time framework, is represented by the drift term.[3] In the discrete time framework, the intuition is also straightforward: as rare events, jumps take place only in a small number of days, during which the effect of risk premium on stock returns is inconsequential. Therefore, if two stocks have substantially different systematic risk exposure, the difference in risk premium should result in small but pervasive differences in daily returns. On the other hand, if the return difference is concentrated around only two or three days of a year, it can hardly be attributed

[1] Greenspan, Alan, "We will never have a perfect model of risk," *Financial Times*, March 16, 2008.

[2] See, e.g., Jarrow and Rosenfeld (1984), Bates (2000), Duffie and Pan (2001), Andersen, Benzoni, and Lund (2002), Liu, Longstaff, and Pan (2003), Eraker, Johannes, and Polson (2003), and Aït-Sahalia, Cacho-Diaz and Hurd (2006), among others.

[3] This is not to say that jumps are unrelated to risk premium. Systematic jump risk may be priced and commands a risk premium in the form of continuous drift. Nevertheless, jumps and risk premium remain two distinct components of stock returns.

to risk premium.

This distinction is useful in evaluating various competing explanations of stock return predictability. So far, one of the greatest challenges facing the empirical finance literature is to distinguish rational hypotheses from behavioral ones. Very often, both types of models produce similar predictive patterns in *total* stock returns.[4] However, differences emerge when it comes to the predictability of the jump component vs. the continuous component of stock return. The main premise of rational asset pricing explanations of various "market anomalies" is the effect of risk premium, in either unconditional or time-varying conditional form. For example, Fama and French (1992, 1996) hypothesize that both size and book-to-market effects are due to risk exposure that is not captured by market beta. In Johnson (2002), momentum arises as a result of predictable increase in risk and risk premium after positive cash flow news. By contrast, in a typical behavioral proposition, investors misreact to cash flow information contained in a firm-specific variable. Consequently, when such information is later released to the market in a conspicuous way (such as earnings announcements or profit warnings), investors may respond dramatically, causing stock price jumps.[5] By disentangling predictability in jumps from that in continuous return component, our study provides a new perspective for understanding this important on-going debate in asset pricing literature.

From a methodology point of view, separating the jump component from total returns also helps to address a well-known problem in empirical asset pricing literature, i.e., realized return can be a poor proxy for expected return; see, e.g., Elton (1999). Elton (1999) points out that of particular concerned is the influence of large information surprises (or jumps) on realized

[4]For example, Brav and Heaton (2002) demonstrate that an economy with structural uncertainty and rational Bayesian investors may generate asset price dynamics similar to a market populated by investors misreacting to information. Li, Livdan, and Zhang (2008) show that a large number of market anomalies related to firms' profitability, investment and financing activities can be reconciled with a neo-classical model of corporate investments.

[5]We note that behavioral biases do not necessarily lead to stock price jumps. In other words, an association between return predictability and jumps is not a necessary prediction of behavioral hypotheses. This is because the correction of mispricing can take the form of either diffusion (if the information investors initially mis-react to transpires in the market gradually), or jumps (when such information arrives in lump sum). Nevertheless, there are strong institutional and legal reasons to believe that lumpy information arrival is becoming more of a norm than an exception, especially with recent regulations on corporate information disclosure, e.g., Reg FD.

returns, and suggests two solutions – (1) identifying all information announcements and then adjusting for surprises, or (2) developing econometric techniques to identify large surprises without directly observing announcements. Several existing studies are essentially in the spirit of the first solution, by examining stock return predictability around a particular informational event – earnings announcement. For instance, Bernard and Thomas (1989), Jegadeesh and Titman (1993), Sloan (1996), and Titman, Wei, and Xie (2004), among others, show that firm-specific variables such as earning surprises, past returns, accounting accruals, and capital expenditure can predict stock returns around future earnings announcement dates. Intuitively, if predictable returns are concentrated around earnings announcements, then they are unlikely a form of risk compensation. Similarly, Baker, Litov, Watcher, and Wurgler (2005) use earnings announcement returns of stocks traded by mutual funds as a "model-free" way to measure fund managers' stock selection ability. The approach employed in this paper is in line with the second solution of Elton (1999), i.e., separating jumps out of total returns. Meanwhile, our approach can also be viewed as a generalization of the studies using earnings announcement returns. As our analysis shows, there are many types of informational events, in addition to earnings announcements, that can cause large surprises to investors.

To identify jumps in individual stock prices, we extend the jump testing methods proposed in recent literature, namely the "variance swap" approach of Jiang and Oomen (2007). The method is based on an intuition long established in the finance literature: in the absence of jumps, the difference between simple return and log return equals one half of the instantaneous return variance.[6] However, when there are jumps in the price process, this replication strategy fails and the replication error is a function of realized jumps. This result forms the basis of the variance swap approach for identifying jumps. The approach is model-free, as it does not require parametric specifications of drift, diffusion, or jump. A further advantage is its computational ease when applied to a large cross-section of stocks. Simulations confirm that this method is powerful in identifying jump returns for the purpose of this study.

We apply the jump estimation technique to the CRSP daily stock return data over a long period from July 1927 to June 2005. For an average stock, there are 2.07 jumps per year with comparable magnitude for positive and negative jumps. However, positive jumps occur much

[6]Relying on this relation, Neuberger (1994) proposes a strategy to replicate "variance swap" – a contract with payoff determined by realized variance.

more frequently. For an average stock, there are 1.37 positive jumps vs. 0.71 negative jumps per year. As a result, the cumulative jump returns are on average positive. This is an interesting contrast to the prevalently negative jumps in market indexes. Our analysis further shows that jumps in individual stock prices tend to be idiosyncratic, and the predominance of positive jumps is not due to dramatic reduction in expected returns, firms' financial leverage, or growth options.

When examining the relation between jumps and cross-sectional return predictability, we focus on five well-known anomalies documented in the literature, from the classical size, value, and momentum effects, to the recently documented net share issuance effect and liquidity premium. We find that the size and liquidity effects are fully driven by jumps. When stocks are sorted into equal-weighted quintile portfolios based on size and the Amihud (2002) illiquidity ratio, jumps are substantially larger for small-cap and low-liquidity stocks than for large-cap and high-liquidity stocks. The differences in jumps are sufficient to account for the total return differences between top and bottom quintiles. In contrast, the differences in the continuous return component between the top and bottom quintiles are statistically insignificant. Jumps also contribute partially to the value premium – the differences in both jump component and continuous return component between the top and bottom book-to-market quintiles are significantly positive. On the other hand, the momentum effect is not realized through jumps. In fact, past losers tend to have more positive jumps than past winners. Finally, there is no significant relation between net share issuance and jumps. The total return spread between stocks in the top and bottom net share issuance quintiles is completely due to the difference in continuous return component.

We further show that the patterns are robust to variations in jump return estimation and return predictability analysis. For example, we also estimate jumps at different critical levels, performing jump tests over different horizons, and using extreme stock returns as proxy for jumps. In addition, we investigate the relation between return predictability and jumps by constructing value-weighted instead of equal-weighted portfolios, partitioning samples into stocks with jumps and those without jumps, and using Fama-MacBeth regressions instead of sorted-portfolio approach. The only notable difference is that based on value-weighted quintile portfolios, the value premium is fully driven by jumps.

The fact that the return-predictive power of size, book-to-market ratio, and liquidity is partially or completely driven by jumps is at odds with a simple risk premium story. We further explore several alternative hypotheses to reconcile our results within the rational asset pricing paradigm. Our first conjecture is that in a rational model, expected jumps are compensated by an offsetting term in continuous drift (i.e., the martingale restriction on jumps). As such, jumps and the offsetting drift term combined will have no effect on the predictable total stock returns, and risk premium remains the driving force of return predictability. Second, we hypothesize that investors demand more compensation for stocks with large jumps. The cross-sectional return differences associated with size, value and liquidity may be simply the effect of compensation for jump risk. Since jumps are closely related to return skewness, we also consider the effect of investor preference for skewness on stock return predictability. The third hypothesis is that jumps in stock prices may be due to discontinuity in expected return as a result of dramatic changes in risk exposure associated with firm characteristics. For example, relative to large firms, small firms may be more likely to have sudden large reduction in risk through the exercise of growth options, resulting in positive stock price jumps.

However, none of the three hypotheses is fully consistent with the data. Under the first hypothesis, if jumps are not the driving force of return predictability, then controlling for expected jumps should not significantly affect the return predictive power of size and liquidity. Instead, we find that once we control for the jump effect in the drift component, there is no longer significant return predictability based on size or liquidity. Concerning the second hypothesis, we find that jump risk fails to predict stock returns at the annual horizon, and after controlling for jump risk, predictability in jumps remains the driving force of the size and liquidity effects. In addition, we find that investor preference for return skewness cannot explain the documented relation between jumps and return predictability. Finally, under the third hypothesis, if the size, value, and liquidity effects are caused by discontinuity in expected return, then small, value, and illiquid stocks should experience substantial decrease in expected return after positive jumps. We do not find this pattern in the data.

The rest of the paper is structured as follows. Section II provides a review of stock return predictability and details of variable construction. Section III describes the statistical procedure for identifying jumps. Section IV presents empirical results on jumps and stock return predictability. Section V performs further analysis on alternative rational explanations. Section VI concludes.

II. Stock Return Predictability: Literature and Variable Construction

In this study, we focus on five anomalies, namely, the classical size, value, momentum effects, and two anomalies in recent spotlight, the net share issuance effect and the liquidity premium.[7] We choose these anomalies for two reasons. First, these anomalies suggest that cross-sectional stock returns are predictable at the relatively long horizon of one year – as opposed to a daily or weekly horizon over which the risk premium effect is typically small. Second, the underlying variables associated with these anomalies are available over a long sample period, from 1927 to 2004. In the following, we first briefly review existing studies on these five anomalies and then describe in detail the construction of return-predictive variables.

II.A. Related Literature

The size effect and value effect are among the earliest market anomalies documented by academic studies. Banz (1981), Reinganum (1981), and many subsequent studies show that small firms tend to earn higher returns than large firms, and that the size premium cannot be explained by the standard CAPM. Similarly, Fama and French (1992), among others, find that firms with higher book-to-market ratios earn higher returns, and the return differences cannot be explained by CAPM. Lakonishok, Shleifer, and Vishny (1994) argue that the value premium is due to investors' excessive extrapolation of past performance when valuing stocks. Therefore, the book-to-market ratio is regarded as a contrarian indicator. On the other hand, researchers from the rational camp point out that both size and value effects are due to compensation for bearing systematic risks omitted in traditional asset pricing models. For example, Chan and Chen (1988) and Fama and French (1992; 1996) argue that smaller firms and higher book-to-market ratio firms have higher exposure to systematic distress risk. This motivates the three-factor asset pricing model of Fama and French (1996). Berk, Green, and Naik (1999) provide a conditional asset pricing model to interpret these two effects, based on the risk dynamics of small firms and

[7] In Appendix C, we report the results for all 20 variables considered in our study. These variables fall into one of the following nine categories: size, value, momentum, earnings quality, growth, financing, intangible investments, profitability, and liquidity. Details on variable definition and construction are available upon request.

growth firms that are related to the growth options. In addition, Zhang (2005) links the value effect to investment adjustment cost and counter-cyclical price of risk, using the intertemporal CAPM framework.

Stock price momentum is documented by Jegadeesh and Titman (1993), who find that stocks with higher past returns subsequently earn higher returns, at horizons ranging from 3 to 12 months. Fama and French (1996) show that momentum is not subsumed by the size or value effects. Several studies have proposed behavioral explanations for the momentum effect, based on investor mis-reaction to information (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)) or irrational investor preference (e.g., Grinblatt and Han (2005)). On the other hand, Johnson (2002), using a rational asset pricing model, shows that momentum is consistent with time-varying risk and time-varying expected return. Yao (2008) reports that momentum is driven by a small number of dynamic systematic factors not captured by classical factor models.

A number of studies on corporate events find that stock prices drift downward following initial public offers and seasoned equity offers (e.g., Ritter (1991), Loughran and Ritter (1997)), and drift upward after stock repurchases (e.g., Lakonishok and Vermaelen (1990), Ikenberry, Lakonishok, and Vermaelen (1995)). Daniel and Titman (2006) use net share issues, i.e., changes in shares outstanding, to summarize these activities and show that net share issuance is negatively correlated with future stock return. Pontiff and Woodgate (2008) provide further evidence on this effect. Bradshaw, Sloan and Richardson (2006) define a similar net equity financing variable and show that this variable negatively predicts stock returns. A typical behavioral view of this anomaly is that firms time their equity financing activities to exploit market mispricing of stocks and investors under-react to information signaled by managerial actions. On the other hand, Li, Livdan, and Zhang (2008) provide a rational model of corporate investments. In their model, corporate financing and investment activities lead to lower expected stock returns as a result of decreasing return to scale. A similar dynamic equilibrium model is provided by Carlson, Fisher, and Giammarino (2006).

It is also well documented that illiquid stocks earn higher returns than liquid stocks, see, for example, Amihud and Mendelson (1986), Brennan and Subrahmanyan (1996), Eleswarapu (1997), Datar, Naik, and Radcliffe (1998), and Amihud (2002). Measures of liquidity or illiquidity range from trading turnover, dollar trading volume, Amivest liquidity ratio, and Amihud illiquidity ratio, to various components of transaction costs based on microstructure data, such as bid-ask spread and price impact. Amihud and Mendelson (1986) provide a theoretical model to show that liquidity premium is a form of compensation for holding illiquid securities.[8] A recent stream of literature (e.g., Pastor and Stambaugh (2003); Acharya and Pedersen (2005)) further argues that systematic liquidity risk is priced in the cross-section of stock returns. While there is no direct behavioral proposition for this phenomenon, studies have debated on whether the magnitude of the liquidity premium is too high to be justified by rational asset pricing models (e.g., Constantinides (1986), Vayanos (1998), and Jang, Koo, Liu, and Lowenstein (2007)).

II.B. Variable Construction

Based on the above-discussed market anomalies, we construct five return-predictive variables, namely, SIZE, BM, MOM, NS, and ILLIQ.

- SIZE: the natural log of market capitalization (from CRSP) at the end of June of year t.
- BM: the natural log of the book to market ratio. Following Fama and French (1993), book value of equity is stockholders' equity plus balance-sheet deferred taxes and investment tax credit (Compustat item 35), if available, minus preferred stock liquidating value (item 10), if available, or redemption value (item 56), if available, or carrying value (item 130). Depending on availability, stockholders' equity is Compustat item 216, or 60+130, or 6-181, in that order. All Compustat items are measured for the fiscal year ending in calendar year t-1. For the period prior to 1950, during which the Compustat data is not available, we obtain the data on book value of equity from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french). The market value of equity is stock price times shares outstanding at the end of December of year t-1, from CRSP. For firms with non-positive book value of equity, BM is treated as missing.
- MOM: the 11-month buy-and-hold return from July of year t-1 to May of year t, from CRSP. This measure of price momentum follows, for example, Fama and French (2008). If there are less than 11 monthly return observations available, MOM is treated as missing.

[8] Although compensation for illiquidity is different from compensation for risk, in continuous-time models it is similarly represented by the continuous drift, not jumps.

- NS: the change in natural log of split-adjusted shares outstanding from fiscal year ending in calendar year t-2 to fiscal year ending in calendar year t-1. The split-adjusted shares outstanding is Compustat shares outstanding (item 25) times the Compustat adjustment factor (item 27). Again, this measure of net stock issues follows Fama and French (2008). For the period prior to 1950, since the Compustat data is not available, we use CRSP split-adjusted shares outstanding at the end of calendar years to compute NS.

- ILLIQ: cross-sectional percentile rank of Amihud (2002) illiquidity ratio. The illiquidity ratio is the absolute value of daily stock return divided by the daily dollar trading volume and then averaged over July of year t-1 to June of year t, with data from CRSP. A minimum of 100 daily observations are required to compute the illiquidity ratio, otherwise ILLIQ is treated as missing. Since trading volume for NASDAQ is defined differently from that for NYSE and AMEX, in each year we cross-sectionally rank the illiquidity ratio, for NYSE/AMEX stocks and for NASDAQ stocks separately, into percentiles.

III. Identifying Jumps in Stock Prices

III.A. Methodology: A Model-Free Approach

A number of statistical tests have been developed to detect the existence of jumps in asset prices. For instance, Aït-Sahalia (2002) exploits the restrictions on the transition density of diffusion processes to assess the likelihood of jumps. Carr and Wu (2003) make use of the decay of the time value of options with respect to maturity. More recently, Barndorff-Nielsen and Shephard (2004, 2006) propose a bi-power variation (BPV) measure to separate the jump variance and diffusive variance based on bi-power variation. Lee and Mykland (2007) exploit the properties of BPV and develop a rolling-based nonparametric test of jumps. Aït-Sahalia and Jacod (2006) propose a family of statistical tests of jumps using power variations of returns.

In this study, we use the variance swap approach recently developed by Jiang and Oomen (2007) to detect the occurrence of jumps. The method is straightforward to implement, and computationally fast when applied to samples with large cross-section and long time series. Simulations in Jiang and Oomen (2007) show that it has desirable finite sample properties in size and power. In addition, simulations in Lee and Mykland (2007) show that the variance swap test has comparable power to their nonparametric test under most of the realistic settings.

The variance swap approach is "model-free" as it applies to the following general asset price processes:

$$dS_t/S_t = \mu_t dt + \sqrt{V_t} dW_t + (\exp(J_t) - 1)\, dq_t(\lambda_t) \tag{1}$$

where μ_t is the drift, V_t is the diffusive variance when there is no random jump, W_t is a standard Brownian motion, q_t is a counting process with finite intensity λ_t $(0 \leq \lambda_t < \infty)$, and J_t is a random jump. There is no particular structure imposed on the drift, diffusive volatility, or the jump component. Applying Itô's lemma, we have the following process for $\ln S_t$:

$$d \ln S_t = (\mu_t - \frac{1}{2} V_t) dt + \sqrt{V_t} dW_t + J_t dq_t(\lambda_t) \tag{2}$$

Therefore, the cumulative difference between the instantaneous simple return (dS_t/S_t) and log return ($d \ln S_t$) over a period can be expressed as:

$$2 \int_0^1 (dS_t/S_t - d \ln S_t) = \int_0^1 V_t dt + 2 \int_0^1 (\exp(J_t) - J_t - 1)\, dq_t \tag{3}$$

It is clear that when there is no jump (i.e. $J_t = 0$), the difference between the instantaneous simple return and log return captures half of the instantaneous variance. However, when there are jumps in stock prices, the difference is also a function of realized jumps.

Suppose that stock prices are observed at time interval δ with N return observations over the period $[0, 1]$, i.e, $\delta = 1/N$. Let $\{r_{\delta i} = \ln(S_{\delta i}/S_{\delta(i-1)})\}_{i=1,\cdots,N}$ denote the observed log returns. It is known that the realized variance measure, $RV_N = \sum_{i=1}^N r_{\delta i}^2$, is a consistent estimator of integrated return variance or quadratic variation (see, e.g., Jacod and Shiryaev (1987) and Andersen, Bollerslev, Diebold, and Labys (2003)): $\operatorname*{plim}_{N\to\infty} RV_N = \int_0^1 V_t dt + \int_0^1 J_t^2 dq_t$. A discretized version of the variance swap measure (i.e., the left-hand-side of (3)) can also be constructed as $SwV_N = 2\sum_{i=1}^N (R_{\delta i} - r_{\delta i})$ where $R_{\delta i} = (S_{\delta i} - S_{\delta(i-1)})/S_{\delta(i-1)}$ is the simple return. By construction, the difference between SwV and RV can be used to test for the presence of jumps. Under the null of no jumps, the following test statistic is proposed in Jiang and Oomen (2007):

$$JS_0 = \frac{V_{(0,1)} N}{\sqrt{\Omega_{SwV}}} \left(1 - \frac{RV_N}{SwV_N}\right) \xrightarrow{d} \mathcal{N}(0, 1) \tag{4}$$

where $V_{(0,1)} = \int_0^1 V_t dt$ and $\Omega_{SwV} = \frac{1}{9}\mu_6 \int_0^1 V_u^3 du$ with $\mu_p = 2^{p/2}\Gamma((p+1)/2)/\sqrt{\pi}$ for $p > 0$. A consistent estimator of $V_{(0,1)}$ is the bi-power variation (BPV) defined in Barndorff-Nielsen and

Shephard (2004): $BPV_N = \frac{1}{\mu_1^2}\sum_{i=1}^{N-1}|r_{\delta,i+1}|\,|r_{\delta,i}|$. And a consistent estimator for Ω_{SwV} is given by $\widehat{\Omega}_{SwV}^{(p)} = \frac{\mu_6}{9}\frac{N^3\mu_{6/p}^{-p}}{N-p+1}\sum_{j=0}^{N-p}\prod_{k=1}^{p}|r_{\delta,j+k}|^{6/p}$.

Once the test rejects the null hypothesis of no jumps, the following procedure is employed to further identify days with stock price jumps.

- Step 1: Let $\{r_1, r_2, \cdots r_N\}$ be log return observations during the testing period. If the jump test statistic JS_0 is significant, we record JS_0 and continue to Step 2.

- Step 2: We replace each return observation $r_i, i = 1, \cdots, N$, by the median of the sample (denoted by r_{md})[9], and perform jump test on return series $\{r_1, \cdots, r_{i-1}, r_{md}, r_{i+1}, \cdots, r_N\}$. A series of test statistic $JS^{(i)}, i = 1, 2, \cdots, N$ are recorded.

- Step 3: We compute the differences of the jump test statistic in Step 1 with those in Step 2, i.e., $JS_0 - JS^{(i)}, i = 1, 2, \cdots, N$. Day j's return (r_j) is identified as the jump return if $JS_0 - JS^{(j)}$ has the highest value among all days. This criterion is in the spirit of the likelihood ratio test since r_j is the return that contributes most to the jump test to reject the null hypothesis in Step 1.

- Step 4: Replace the identified jump, r_j, by the median of returns, and we have a new sample of return observations $\{r_1, \cdots, r_{j-1},\ r_{md}, r_{j+1}, \cdots, r_N\}$. Then start over again from Step 1.

The above procedure (Step 1 to 4) continues until the null of no further jumps is no longer rejected by the JS_0 statistic.

Daily stock returns contain market microstructure noise. We take this into account in both jump test and jump identification. Specifically, the jump test is modified with the assumption that stock prices are observed with noise. That is, $\ln S_{i\delta}^* = \ln S_{i\delta} + \epsilon_i$, for $i = 1, \cdots, N$, where $\epsilon_i \sim iidN(0, \sigma_\epsilon)$. The standard deviation of the noise (σ_ϵ) is estimated from autocovariance of observed stock returns and used to adjust the asymptotic variance of the jump test. Details can be found in Jiang and Oomen (2007). In addition, to ensure that identified jump returns are not the result of bid-ask bounce or the effect of non-trading, we impose additional restrictions.

[9] In a similar procedure proposed by Andersen, Bollerslev, Federiksen and Nielsen (2007) to identify jumps, they replace each return by the mean of remaining $N-1$ returns.

First, the absolute value of identified jump return must be more than twice the tick size. We find that this restriction has almost no effect on identified jumps. Second, we exclude those jumps where there is no trading on that day or during any of the previous three trading days. A no-trading day is defined as one if the daily trading volume is zero or missing in CRSP. This restriction reduces the non-trading effect on the jump identification.[10]

III.B. Simulations

The most relevant issue for our study is the accuracy of jump return estimation – the cumulative jumps realized over a period of time (e.g., 12 months). In this section, we perform simulations to assess the accuracy of the estimation procedure. Details of the simulation procedure are described in Appendix A. Stock prices are simulated using a model with stochastic volatility and jumps, taking into account the following features. First, the stock price path is simulated at the 10-minute intraday interval. To be consistent with our empirical estimation procedure, however, we identify jumps based on daily return observations. Second, the model parameters are calibrated to the CRSP daily stock return data to reflect the realistic features of the stock return process. That is, we take into account the cross-sectional differences in stock price dynamics, such as the level of volatility and the volatility of volatility. In addition, jumps in the simulated return process are randomly drawn from the identified jumps in our empirical analysis. Thus, the jumps we incorporate into the simulated returns have the same distribution as those identified from the data. Third, the simulations also take into account market microstructure noise in terms of serial correlations in stock returns induced by bid-ask bounce. Finally, alternative model specifications are also considered.

The simulation results, summarized in Table A in Appendix A, show that the proposed procedure results in rather accurate estimation of jump returns. As discussed in Appendix A, while the jump test has imperfect power in detecting jumps, it has a much lesser effect on the accuracy of jump return estimation. As shown in Appendix A, the average absolute errors of estimated jump returns are small compared to the actual magnitude of jumps.

[10] We do not impose this restriction for NASDAQ stocks prior to 1982 since daily trading volume is not available for these stocks in CRSP. Nevertheless, we confirm that the results do not change substantially whether or not the restriction is imposed.

IV. Empirical Analysis

We start with all common stocks in the CRSP data in June of each year from 1927 to 2004, but excluding those without valid market capitalization or with price less than $5 at the end of the portfolio formation period (i.e., at the end of June). This is to avoid market microstructure issues in measuring returns and to minimize the effect of transaction costs when evaluating return predictability. Further, following the convention of existing studies involving accounting data (e.g., Fama and French (1992)), we exclude financial firms (Standard Industrial Classification codes between 6000 and 6999 in CRSP) in our reported results, although we find that including financial firms does not substantially change these results. The resulting stock sample is referred to as the "stock universe".

IV.A. The Cross-Section of Stock Price Jumps

IV.A.1. Summary Statistics of Individual Stock Price Jumps

From July 1927 to June 2005, in each calendar quarter we identify jumps based on daily stock returns for all firms in the above-described stock universe. Our main results are based on jumps identified at the 1% critical level. To ensure the robustness of the jump test, we require at least 44 (or two months) daily return observations during the quarter.

Table I reports summary statistics of jumps. For each stock, jump frequency is calculated as the ratio of total number of jumps to the total number of years the stock is in our sample. Jump size is the average of all realized jumps, expressed in *log return* form. We then obtain statistics on the cross-sectional distributions of jump frequencies and sizes.

During the entire sample period (July 1927 to June 2005), we identify 327,457 jumps. Across stocks, the mean and median jump frequencies are 2.07 and 2.00 per year. The mean and median jump sizes are positive, at 2.51% and 3.05%, respectively. To further understand the cross-sectional distribution of jumps, we provide cross-sectional statistics for positive and negative jumps separately. Positive (negative) jump frequency is the ratio of the total number of positive (negative) jumps to the total number of years the stock is in our sample. The positive (negative) jump size is the average of all realized positive (negative) jumps. The average size of positive jumps is slightly smaller in magnitude than that of negative jumps: 12.74% vs.

-15.25%. However, positive jumps are much more frequent than negative ones: there are on average 1.37 positive jumps vs. 0.71 negative jumps per year. This pattern is consistent in the two subperiods – 1927/07 to 1962/06 and 1962/07 to 2005/06.

The statistics confirm that jumps are indeed rare events. Also interestingly, jumps in individual stock prices are more often positive than negative, an interesting contrast to the pattern for market portfolios. Existing studies, for example, Andersen, Benzoni, and Lund (2002), and Chernov, Gallant, Ghysels, and Tauchen (2003), find the mean jump size of the S&P 500 index to be negative. This pattern is also confirmed when we perform the jump test for the value-weighted CRSP index. For a total of 78 years from July 1927 to June 2005, there are 109 identified jump days for the CRSP index, among which 45 jumps are positive and 64 negative. The mean jump size is -1.02%, and the mean positive and negative jump sizes are respectively 2.88% and -3.76%.[11]

To see how often jumps in individual stocks concur with market jumps, we find that on those 109 days with jumps in market portfolios, there are 9,180 concurrent jumps in individual stock prices. This represents a very small percentage of all 327,457 identified jumps. Therefore, most individual stock price jumps are idiosyncratic. Further, the average size of individual stock price jumps taking place on the market jump days is -4.00%, and 64.84% of such jumps are negative.

We also identify the days during which a large number of stocks have jumps. For the entire sample period from 1927 to 2005, there are only 42 days where more than 5 percent of the sample stocks experience jumps together.[12] The mean jump size during these days is -5.57%, with 74.80% of jumps being negative.

It is already well known that daily returns to market portfolios exhibit negative skewness, while daily individual stock returns exhibit positive skewness (e.g., Campbell, Lo and MacKinlay (1997)). In theory, skewness can be due to multiple reasons, such as jumps, stochastic volatility, and nonlinear drift. Empirical studies such as Andersen et al (2002) suggest that jumps are important in explaining the negative skewness of market returns. The evidence documented in our study further suggests that jumps are likely an important – perhaps dominant – source of

[11] As an additional note, the asymmetry of jump distribution is not altered even if we treat all delisting returns as jumps. While delisting returns are more often negative than positive, delisting is far less frequent than jumps - about 3% of stocks are delisted each year in our stock sample.

[12] Not surprisingly, October 19, 1987, the Black Monday, is one of such days.

positive skewness for individual stock returns. In Appendix B, we provide some further analysis on this. Results based on calibrated models show that it is rather easy for jump-diffusion models (even with constant volatility) to generate the type of skewness in our stock sample, but virtually impossible for pure stochastic volatility models to generate such skewness.

To summarize, jumps in individual stock prices tend to be positive and idiosyncratic, while systematic jumps tend to be negative. Such cross-sectional distribution of jumps is likely the source of the well-observed pattern of positive skewness for individual stock returns and negative skewness for market portfolio returns.

IV.A.2. Why are Jumps Mostly Positive?

The predominantly positive jumps in individual stock prices may explain the positive skewness of stock returns. But what explains the dominance of positive jumps for individual stock prices? The contrast between jumps in individual stock prices and market portfolios immediately rules out the possibility that positive jumps in individual stock prices are driven by systematic factors. In this section, we contemplate on a few other explanations.

First, in the present value framework (e.g., Campbell (1991)), jumps in individual stock prices can be caused by large shocks to cash flows and/or large changes in discount rate. Large changes in discount rate can in turn be caused by large changes in systematic risk exposure. For example, it is possible that information released by a firm (e.g., earnings announcement) could substantially reduce systematic uncertainty about the trajectory of future cash flows, thereby reducing the expected return, and resulting in positive stock price jumps.

If reduction of risk is the reason for predominantly positive stock price jumps, then the expected return after a large positive stock price jump should on average be lower than prior to the jump. We perform an empirical test on this hypothesis, using realized returns as proxy for expected returns. Let JR_{it} denote the jump return of stock i during month t. Let $\mathrm{TR}_{i,t+1,t+12}$ be the total stock return for the 12 months immediately after month t, and $\mathrm{TR}_{i,t-12,t-1}$ be the total stock return for the 12 months immediately before month t. We estimate change in expected return before and after jump by $\Delta TR_{it} = \mathrm{TR}_{i,t+1,t+12}$-$\mathrm{TR}_{i,t-12,t-1}$. In each sample year we perform the following Fama-MacBeth regression:

$$\Delta TR_{it} = a + b \times \mathrm{JR}_{it} + e_{it} \tag{5}$$

Multiple jumps of the same stock in one sample year are treated as multiple observations in this regression. The time series average of the coefficients for JR_{it} is 0.31, with a time-series t-statistic of 2.03. The significantly positive coefficient suggests that after positive jumps, expected return (as proxied by total return) tends to be higher than before jumps, inconsistent with the effect of substantial risk reduction. As a robustness check, we also perform the above regression using the change in the continuous return component (ΔCR_{it}) as dependent variable, where ΔCR_{it}= $\text{CR}_{i,t+1,t+12}$-$\text{CR}_{i,t-12,t-1}$, and $\text{CR}_{i,t+1,t+12}$ ($\text{CR}_{i,t-12,t-1}$) is the continuous component of stock return during 12 months after (before) month t. We obtain similar results, with a mean coefficient of 0.29 for JR_{it} with a t-statistic of 1.98. In addition, using a panel data regression approach with both firm and time effects yields similar results.

Alternatively, the predominance of positive jumps could be due to nonlinear dynamics in stock returns. Examples of such nonlinearity include the effects of financial leverage and growth options. For leveraged firms, stocks are priced as call options on the underlying firm assets. As such, jumps in stock prices may be asymmetric even when jumps in firms' underlying asset value are symmetric. Further, even when there is no financial leverage, stock returns could still have option-like features due to growth options. To test this, we rank firms according to their financial leverage, and compare the distribution of jumps across ranks.[13] In untabulated analysis, we find a slightly "U-shaped" relation between the frequency of positive jumps and financial leverage. The dominance of positive jumps is as strong for firms with little or no leverage as for firms with high leverage. Similarly, we sort firms based on the book-to-market ratio, a commonly used proxy for growth options. Contrary to the hypothesis, we find that it is firms with high book-to-market ratio – those considered to have low growth options – that are more likely to experience large positive jumps. Therefore, neither financial leverage nor growth option seems to be the explanation.

Having ruled out explanations such as the effect of systematic jumps in market index, large reduction of discount rate, and optionality in stock returns, we are left with one interpretation – asymmetric shocks to firm-specific cash flows. That is, extreme cash flow shocks may be more often positive than negative.[14] However, the exact mechanism behind such asymmetry is not

[13]Leverage is computed as the ratio of long-term debt (Compustat annual data item 9) plus debt in current liabilities (item 34) to total assets (item 6).

[14]In addition, one may link stock price jumps to liquidity shocks (i.e., the price impact due to uninformed

quite clear. Several empirical studies have documented that announced earnings are often higher than consensus analyst forecasts (e.g., Degeorge, Patel, and Zeckhauser (1999), and Richardson, Teoh, and Wysocki (2004)). Frazzini and Lamont (2006) find that stock returns around earnings announcements tend to be positive. However, these studies have not examined the frequency of extremely positive or negative earnings shocks.

It is also possible that the asymmetry of jumps is not due to the cash flow process per se, but rather due to the way cash flow information is propagated to the market. Contemplating on the cause of strong positive skewness of small stock returns, Chen, Hong, and Stein (2001) hypothesize that corporate managers may use their discretion to disclose good news to investors immediately, while allowing bad news to dribble out slowly. This is a promising avenue. Nevertheless, providing empirical links between jumps and corporate disclosure behavior is beyond the scope of this paper and is left for future research.

IV.B. Cross-Sectional Stock Return Predictability

IV.B.1. Summary Statistics of Firm Characteristic Variables

Table II provides summary statistics on the five return-predictive variables defined in Section III.B. In Panel A, we report the number of stocks, the cross-sectional mean, median, 5th, 25th, 75th, and 95th percentiles, and standard deviations of each variable for five representative years over our sample period: 1927, 1940, 1960, 1980, and 2004. Calculation of the illiquidity ratio involves daily trading volume, which becomes available for NASDAQ stocks after 1982. Therefore statistics on the illiquidity ratio for NASDAQ stocks are separately reported for 2004. In any given year, there are a large number of stocks with NS=0 (i.e., no share issuance or repurchase activities). To ensure that the quintile portfolios are well defined, we exclude stocks with zero-NS when forming NS quintiles. As shown in the table, the number of stocks with non-zero NS is substantially smaller than the whole sample, especially in the early years of 1927 and 1940.

In Panel B, we report the time series averages of cross-sectional correlations among the five

large transactions). If sudden surges of liquidity-motivated trades are more often on the buy side than on the sell side, stock prices could also exhibit more frequent positive jumps. To our knowledge, there has been no theoretical model or empirical evidence supporting such patterns of liquidity shocks.

variables. The statistics are reported for the entire sample period (1927-2004), as well as for two subperiods: 1927-1961, and 1962-2004. The correlations are generally low among these variables except that ILLIQ is highly negatively correlated with SIZE. Amihud (2002) shows that, even with the high correlation, the illiquidity ratio and firm size do not subsume each other in predicting returns. We note that the purpose of this paper is not to pinpoint the relation between the size anomaly and the liquidity premium. Rather, we are interested in whether any of them is related to jumps in stock prices.

As mentioned earlier, we select the above five variables because they can be constructed using data over a very long sample period and they have return-predictive power at the annual horizon. As a result, we have left out many variables that either have return-predictive power but are unavailable for the earlier part of the sample period (e.g., those involving Compustat data), or are available for the long sample period but do not have return-predictive power at the annual horizon, such as trading turnover, return volatility, and idiosyncratic volatility – we find that these variables can predict returns only at shorter horizons (e.g., monthly or quarterly). The only exception is the dollar turnover measure (dollar trading volume divided by shares outstanding), which is available for the entire sample period and negatively predicts future one-year return. However, as we discuss in Section IV.C.2., it behaves very similarly to the illiquidity ratio in predicting returns and jumps.

IV.B.2. Return Predictability: Evidence from Quintile Portfolios

We use sorted portfolios to examine the return-predictive power of these five variables. In June of each year t from 1927 to 2004, we sort stocks in our stock universe into equal-weighted quintile portfolios based on each of the five variables. The portfolios are held from July of t to June of t+1, and are rebalanced annually. When computing holding-period returns, we include the delisting returns from CRSP. Following Shumway (1997), when the CRSP delisting return is missing, we replace it with -30% if delisting is performance-related, and zero otherwise.

Table III reports the average annual returns to the sorted portfolios as well as the average numbers of stocks of each portfolio. For the entire sample period from 1927/06 to 2005/06, four out of five variables produce significant spreads between top-bottom quintile returns: SIZE, BM, NS, and ILLIQ. The return spread for the momentum variable MOM is positive but not significant. We find that this is not due to the specific way of computing momentum, after experimenting with alternative momentum measures. Rather, there is no momentum effect during the first subperiod of 1927/07-1962/06. The fact that momentum trading is not profitable during early years in the US stock market is also noted by Jegadeesh and Titman (1993).

As shown in Table III, all five variables produce significant quintile return spreads in the second subperiod from 1962/07 to 2005/06. In comparison, overall stock return predictability is weaker in the first subperiod (1927/07 to 1962/06), during which only two out of the five variables produce significant quintile spreads: BM and ILLIQ. The insignificant NS quintile spread during the first subperiod is not surprising because the average number of stocks in the NS quintile portfolio is especially small. The same pattern is noted by Pontiff and Woodgate (2008). The insignificant SIZE quintile spread is consistent with Davis, Fama, and French (2000), who report insignificant average return to the SMB factor prior to 1963. However, ILLIQ quintile spread is significant, suggesting that SIZE and ILLIQ are different in predicting returns even though they are highly correlated. The significant return-predictive power of ILLIQ in early sample years has not been documented in prior literature.

IV.C. Jumps and Return Predictability

IV.C.1. Jump and Continuous Components of Quintile Portfolio Returns

In Table IV, we report the contributions of jumps and continuous returns to the total returns of quintile portfolios sorted on each of the five variables. To estimate jump returns (JR) for individual stocks, we first sum up all realized jumps (in log return form) over the 12-month holding period (from July of year t to June of year $t+1$), and then convert the jump returns to simple return form. For stocks without a jump during the holding period, the jump return is zero. The continuous component of return (CR) is calculated as the difference between total buy-and-hold return and jump return. The jump and continuous return components for individual stocks are then averaged within each quintile.

For the entire holding period (1927-2005), stock price jumps tend to be overall positive across all quintiles. Jump returns of small stocks, value stocks, past losers, and illiquid stocks are substantially higher than those of large stocks, growth stocks, past winners, and liquid stocks, respectively. Net share issuance does not correlate significantly with jumps.

Jumps fully account for the size and liquidity effects. For SIZE quintiles, the top-bottom spread of jump return is -8.07%, exceeding the total return spread of -5.71%. Strikingly, such a big difference in jump return is only due to about 2 jumps per year on average. In contrast, the spread of continuous return is positive but statistically insignificant, at 2.35%. For ILLIQ quintiles, the pattern is similar. The spread of jump return is 9.55%, significantly positive and with a magnitude exceeding the spread of total return, 7.89%. The spread of continuous return is insignificantly negative, at -1.66%.

Jumps also partially account for the value effect. For BM sorted portfolios, the spread of jump return between the top and bottom quintiles is significantly positive, at 3.58%. However, the spread of continuous return is also significantly positive, at 6.34%.

Jumps do not explain momentum or the net share issuance effect. For MOM quintiles, the top-bottom spread of jump return is in fact negative, whereas the spread of continuous return is not only positive but also exceeds the spread of total return. For NS quintiles, the spread of jump return is close to zero, and the spread of total return is mainly due to that of continuous return.

The results in two subperiods are overall consistent with the above findings. During the first subperiod, for the two variables with significant return-predictive power (BM and ILLIQ), the top-bottom spreads of jumps are significantly positive while the spreads of continuous returns are not significant. During the second subperiod, where all five variables have significant return-predictive power, the jump component of returns explains the quintile return spreads for SIZE and ILLIQ, partially for BM, but not for MOM or NS.

IV.C.2. Robustness Checks

We first perform various robustness checks with variations in the jump testing procedure. First, we change the critical level of the jump test from 1% to 5%. Second, we change the jump testing horizon from quarterly to annually. Third, we use extreme returns (e.g., daily log returns more than 2.58 standard deviations away from the mean) as proxy for jumps. Fourth, we treat all delisting returns as jumps. Finally, we relax the restrictions related to bid-ask bounce and the effect of non-trading imposed in the jump identification procedure (see Section III.A). None of these variations in jump identification procedures substantially alter the conclusions.

We also use alternative methods to examine the relation between jumps and return predictability. Since in each quintile there are always a substantial number of stocks without jumps, to sharpen our inference we further separate stocks in each quintile portfolio into two groups: those with jumps during the 12-month holding period and those without. We then calculate average stock returns for quintile portfolios in each group separately. The results are reported in Table V. We find that the size premium and liquidity premium are only present for stocks with jumps, but absent for stocks without jumps. During the second subperiod, the value premium is present for stocks with jumps, but insignificant for stocks without jumps.

We also use value-weighted portfolios instead of equal-weighted portfolios to evaluate return predictability and the role of jumps. The results are reported in Table VI. The role of jumps is even more important in explaining difference in return to value-weighted portfolios, compared to equal-weighted portfolios. In particular, jumps fully explain the value-weighted BM quintile return spread, even during the second subperiod of 1962/07-2005/06. This suggests that jumps have more power to explain the BM effect among large stocks than among small stocks.

In addition, we perform Fama-MacBeth regression instead of sorted portfolios. Specifically, in each year we perform cross-sectional regressions of the total stock return, the jump return, and the continuous return against each of the five return-predictive variables. The results (untabulated) confirm the findings based on sorted portfolios: jumps explain the return-predictive power of SIZE and ILLIQ, and partially explain that of BM.

Finally, we use dollar turnover as an alternative measure of liquidity, and find that similar to the results based on Amihud (2002) illiquidity ratio (ILLIQ), the return-predictive power of dollar turnover is fully explained by its ability to predict jumps.

IV.C.3. Jumps and Earnings Announcements

Having documented a robust relation between jumps and stock return predictability, an interesting question is whether such relation simply captures the effect of a particular informational event, such as earnings announcement. In this section, we examine the relation between jumps and informational events.

First, we examine returns around earnings announcement. Earnings announcement dates are from Compustat quarterly file, for the period from July of 1974 to June of 2005. We focus on this sample period because announcement dates prior to 1974 are sparse in Compustat. During this sample period, there are 33,9629 quarterly earnings announcements and 22,1327 identified jumps for firms in our stock universe. Therefore, jumps are less frequent than earnings announcements. Among these jumps, 30,651 take place during the four trading-day window of the announcement date (beginning two trading days before and ending one trading day after).[15] That is, only 13.85% of all jumps can be attributed to earnings announcements, and 9.02% of earnings announcements result in stock price jumps.[16]

We then examine whether returns due to earnings announcements play the same role as jumps in explaining return predictability. Earnings announcement returns are calculated as the buy-and-hold returns during the four trading-day window. We then compound the announcement returns during the 12-month holding period (July of year t to June of year t+1). Non-announcement return is calculated as the difference between the total return during the 12-month holding period and the compounded announcement return.

The average total returns, announcement returns, and non-announcement returns for quintile portfolios are reported in Table VII. For SIZE-sorted quintiles, the top-bottom spread in earnings announcement return is insignificantly negative, while that for non-earnings announcement return is significantly negative. For BM-sorted, NS-sorted, and ILLIQ-sorted quintiles, the spreads in both the announcement return and non-announcement return are significant. For MOM-sorted quintiles, only the non-announcement return spread is significant. For comparison we also report the spreads of jump return and continuous return for this sample period. The results on jump and continuous returns are similar to those for the second subperiod of 1962 to 2005. The results show that jumps and earnings announcement returns have substantially different power in explaining return predictability.

Finally, given that earnings announcements are not the only source of stock price jumps, we perform a search on news to see what other types of informational events are associated with jumps. We select several individual stocks and obtain corporate news about these companies from Factiva which offers a comprehensive news collection from authoritative sources including The Wall Street Journal, The Financial Times, Dow Jones and Reuters newswires, and the

[15] In the case that an announcement date is not a trading day, we define the effective announcement date as the trading day immediately after the announcement date. In addition, the results of subsequent analysis are robust to the use of a three-day or five-day window.

[16] Many earnings announcement dates in Compustat are missing, especially for small stocks. This implies that there is potentially a higher percentage of jumps associated with earnings announcements, but at the same time it also implies a lower percentage of earnings announcements causing jumps.

Associated Press. A majority of the jumps of the individual stocks can be related to news. The search confirms that indeed there is a large and diverse set of informational events that trigger stock price jumps. Such events range from earnings announcements, dividend announcements, announcements of merger and acquisition, changes of analyst recommendations or earnings forecasts, to news about other firms in the same industry, and news about macroeconomic conditions or market conditions. To this end, the effort of identifying and analyzing jumps is not in vain even when earnings announcement returns are readily available.

V. Exploring Alternative Rational Explanations

The fact that stock return predictability associated with certain firm characteristics are realized through jumps does not necessarily overthrow the rational asset pricing paradigm. While the evidence is at odds with the simple effect of risk premium, there may exist other rational explanations. It is possible that stock return dynamics has a rather complex structure that allows for such patterns in cross-sectional jumps. Below, we consider three alternative interpretations of the results within the rational asset pricing framework. The first hypothesis is that jumps are anticipated and compensated through an adjustment in the drift. The second hypothesis links stock return predictability to the effect of jump risk premium and investors' preference for skewness. Finally, we consider a hypothesis that predictable jumps in stock prices are the result of dramatic changes in expected returns.

V.A. Martingale Restriction on Jumps: Offsetting Effect in the Drift

So far our analysis has been based on a general stock price process in (1), without any rational restrictions. Now, consider a specific restriction imposed in many rational continuous-time models for stock returns: the martingale property of jumps, which suggests that the instantaneous drift of stock i's price process in (1) takes the following form:

$$\mu_t = r_{f,t} + \Gamma_t - E_{t_-}[(\exp(J_t) - 1)dq_t] \tag{6}$$

where r_f is the risk-free rate, and Γ_t denotes the premium for non-diversifiable risk. The last term, the negative of expected instantaneous jump $E_{t_-}[(\exp(J_t) - 1)dq_t]$, is an offsetting term for jumps, which is often referred to as the "compensator" in the statistics literature (see, e.g., Protter (1990)). When combined with the "compensator", the jump component becomes a martingale because $(\exp(J_t)-1)dq_t - E_{t-}[(\exp(J_t)-1)dq_t]$ has a zero conditional mean. To avoid confusion with "compensation for risk", in this paper we refer to the term $E_{t-}[(\exp(J_t)-1)dq_t]$ as an "offsetter". Under the above specification, expected jumps are offset by the drift, and the expected return is $E(r_t) = r_{f,t} + \Gamma_t$, independent of jumps.

Under this restriction, if investors are fully aware that SIZE, BM, and ILLIQ predict jumps, then the predictable component of jumps should be fully offset by the "offsetter" in continuous drift. Therefore, the cross-sectional predictability of stock return is entirely due to predictable risk premium (Γ_t).[17] In other words, the martingale restriction may sever the link between predictable jumps and predictable total stock returns.

If there is a relation between firm characteristics and risk premium that is at least to some extent independent of the relation between firm characteristics and jumps, then after controlling for jumps, firm characteristics should continue to significantly predict stock returns. We perform the following test on this hypothesis. To control for jumps, we implement a double-sorting procedure. In June of each year t, we first sort stocks into quintiles based on realized jump returns during the holding period from July of t to June of t+1. Stocks without jumps during the holding period are classified into a separate group. Then, within each of the six jump-sorted groups, we further sort stocks into quintiles based on each of the five firm characteristics. Finally, stocks in the same characteristic quintile rank (e.g., in the same size quintile) but across the six different jump groups are combined into a single equal-weighted portfolio. This procedure results in five firm-characteristic portfolios with control for the effect of jumps, and under the "martingale hypothesis" there should be significant difference in returns across these portfolios.

Table VIII reports the average returns of the jump-controlled quintile portfolios. Contrary to the hypothesis, there is no longer significant return differences across SIZE and ILLIQ quintiles, suggesting that the size and liquidity effects are driven by jumps rather than by risk premium.[18]

[17]Note that the continuous return component consists of the drift and diffusion term ($\sigma_t dW_t$). The maintained assumption in rational asset pricing theories is that the diffusion term is unpredictable.

[18]Results in Table V show that for stocks without jumps, size and liquidity do not predict returns. Including these stocks is not crucial for the results in Table VIII. We also perform the analysis by excluding stocks without jumps, and the conclusions remain the same.

BM remains predictive of stock returns, but with a smaller magnitude. On the other hand, controlling for jumps has no significant effect on the predictive power of NS, and enhances the return predictive power of MOM.

We should point out that, in order to reconcile the evidence in Table VIII with the martingale hypothesis, an additional and rather strong assumption is needed. That is, it is necessary to assume a near perfect correlation between risk premium and jump "offsetter", so that in the continuous drift, size or illiquidity related risk premium is exactly offset by expected jumps. Similarly, this assumption is needed to reconcile the martingale hypothesis with the evidence presented in Table IV – that size or illiquidity does not predict the continuous return component. However, to account for such a "coincidental" relation between expected jumps and risk premium requires a rather restrictive asset pricing model.

As a further attempt to isolate the effect of the jump "offsetter" in the continuous drift, we perform another set of analysis. Using the cross-sectional relation between continuous return component and jump component, we directly estimate the jump "offsetter" or expected jumps. We assume that expected jumps are linearly related to realized jumps. Since the jump "offsetter" enters the drift with a negative sign, we perform the following cross-sectional regression of continuous returns (CR) against jump returns (JR):

$$\mathrm{CR}_{i,t+1} - \overline{\mathrm{CR}}_{t+1} = b(\mathrm{JR}_{i,t+1} - \overline{\mathrm{JR}}_{t+1}) + e_{i,t+1} \tag{7}$$

where $\overline{\mathrm{CR}}$ and $\overline{\mathrm{JR}}$ are cross-sectional means of continuous returns and jump returns.[19] The regression is performed in each year and produces significant coefficient estimates. The average coefficient for $\mathrm{JR}_{i,t+1}$ is $\hat{b} = -0.33$ with t=9.59. The fitted value of this regression is the negative of the cross-sectionally de-meaned expected jumps. In other words, the expected jumps, after reverting the sign and then adding back the cross-sectional mean, are given by

$$\widehat{E}(JR_{t+1}) = -\hat{b}(\mathrm{JR}_{i,t+1} - \overline{\mathrm{JR}}_{t+1}) + \overline{\mathrm{JR}}_{t+1} \tag{8}$$

We then infer the expected returns in (6) by adding expected jumps to the continuous drift, i.e., $E[R_{i,t+1}] = CR_{i,t+1} + \widehat{E}(JR_{i,t+1})$.

[19] This procedure ensures that the average estimated E(JR) across stocks equals the average jump returns in the sample. In other words, the unexpected jumps across firms sum to zero, which is a weaker assumption than the martingale restriction.

In Table IX, we report the average estimates of expected jumps and expected returns for stock quintiles sorted on firm characteristics. Indeed, small stocks and illiquid stocks have higher estimates of expected jumps. However, between small and large stocks and between illiquid and liquid stocks, the estimated expected returns are not significantly different.

We also construct other measures of expected jumps using historical information, assuming that expected jumps are a linear function of past jumps, past jump risk, and skewness of past returns. Based on these alternative estimates of expected jumps, we further infer expected returns. The results are similar – size or liquidity does not cause substantial difference in estimated expected return.

V.B. Jump Risk Premium and Investor Preference for Skewness

A further observation from (6) is that the risk premium Γ_t contains compensation for all risk factors, likely including jump risk.[20] Since stocks with large jumps are likely perceived as of higher jump risk, by controlling for jumps in the drift one may have also inadvertently removed the effect of jump risk premium. In this section, we investigate whether it is the jump risk premium that drives the cross-sectional differences in returns.

In addition, jumps are closely related to the skewness of stock returns (see our discussion in Section IV.A.1 and analysis in Appendix B). Several studies have argued that investors may prefer stocks with positive skewness, and therefore skewness should be negatively correlated with expected returns (e.g., Arditti (1967), Scott and Horvath (1980), and Mitton and Vorkink (2006)). We therefore further investigate whether investor preference for skewness can explain our results on the predictability of returns and jumps.

First, we examine if return-predictive stock characteristics are indeed related to jump risk and skewness. Following the literature (e.g., Barndorff-Nielsen and Shephard (2004, 2006)), we measure jump risk based on the difference between realized variance (RV) and bi-power variation (BPV). Both RV and BPV measures are defined in Section III.A. Skewness is measured from daily log returns. Both jump risk and skewness for year t are based on daily returns from July of year t-1 to June of year t.

[20]Existing studies, e.g., Pan (2002), document that there tends to be a negative premium for systematic jump risk.

Table X reports the average jump risk and skewness for stocks in the quintile portfolios formed on one of the five return-predictive variables. Over the entire sample period, the ex ante jump risk is negatively correlated with SIZE and positively correlated with BM and ILLIQ, but has no significant relation with MOM or NS. Return skewness is negatively correlated with SIZE and NS, but positively with BM, MOM and ILLIQ. The results are consistent with the findings in Chen, Hong, and Stein (2001). They document that small stocks, value stocks, and past losers tend to exhibit high positive return skewness. The fact that small, value, and illiquid stocks have high positive skewness is already at odds with the hypothesis that preference for skewness causes the size and liquidity premium. Under that hypothesis, small and illiquid stocks, with high skewness, should command lower expected returns.

Next, we examine the return-predictive power of jump risk and skewness. Using Fama-MacBeth regressions, we find that neither ex ante jump risk nor ex ante skewness can significantly predict stock returns at the annual horizon. For example, when we regress holding-period return against jump risk, the time-series average of the estimated coefficient is -0.10, with a t-statistic of -0.49. When regressing against skewness, the average coefficient is 0.01, with a t-statistic of 1.79.

The above evidence suggests that it is very unlikely for jump risk or skewness to explain the return-predictive power of SIZE, BM, and ILLIQ. This is indeed confirmed using a sequential double-sort procedure. We first sort stocks into quintiles based on jump risk or skewness, and then within each quintile further sort stocks into quintiles based on one of the five firm characteristics (SIZE, BM, MOM, NS, and ILLIQ). Finally, we combine all stocks with the same firm characteristic quintile rank across five jump risk or skewness quintiles, and form an equal-weighted portfolio. These quintile portfolios are essentially formed on firm characteristics after controlling for the effect of jump risk or skewness. The average return spreads of jumps and continuous returns between the top and bottom quintiles are reported in Table XI. Not surprisingly, after we control for either jump risk or skewness, SIZE, BM, ILLIQ continue to predict stock returns and jumps. That is, neither jump risk premium nor investor preference for skewness subsume the role of jumps in explaining return predictability.

We have further constructed measures of co-skewness following Harvey and Siddique (2000) and repeat the above analysis by replacing skewness with co-skewness. In untabulated results, we find that even after controlling for co-skewness, SIZE, BM, and ILLIQ remain predictive of stock returns and jumps.

V.C. Discontinuity in Expected Returns

As mentioned earlier, a possible cause of stock price jump is sudden large changes in expected returns, which may be caused by dramatic changes in the systematic risk exposure of individual stocks. In the following, we investigate whether jumps in systematic risk exposure are the cause of stock return predictability.

To illustrate the relation between changes in systematic risk exposure and stock return predictability, we conjecture the following hypothesis for the size effect. Smaller firms are more likely to have growth options, which often carry higher risk than assets in place. When growth options are exercised (e.g., through capital investments), firms become larger and their risk level reduces. As a result, subsequent expected returns are lower. During the transition, however, stock prices are expected to move higher (due to the reduction in expected return). If growth options are exercised in the form of lumpy investments, then reductions in risk exposure and discount rate may be dramatic, resulting in positive jumps in stock price. To some extent, this can be viewed as an extreme form of time-varying risk analyzed in Berk, Green, and Naik (1999).[21]

In relation to stock return predictability, a testable prediction of the above hypothesis is the following: if predictable jumps associated with size, value and liquidity effects are due to large decreases of risk exposure, SIZE should be *positively* correlated with changes in expected returns after jumps, whereas BM and ILLIQ should be *negatively* correlated with changes in expected returns.

To test this prediction, we calculate the differences in total stock returns and continuous returns between the post- and pre-jump periods for each stock quintiles formed on one of the five firm characteristics. Let ΔTR_{it+1} and ΔCR_{it+1} denote the change in total return and in continuous return for an individual stock. $\Delta TR_{it+1} = R_{it+1} - R_{it-1}$ and R_{it+1} (R_{it-1}) is total

[21]While this hypothesis is ex ante plausible for the size effect, it does not extend to the value or liquidity effects. Intuitively, growth firms are more likely than value firms to experience sudden risk reduction through exercising growth options. Further, there have not been any propositions in the existing literature as to why firms with lower liquidity are more likely to experience jumps in risk exposure.

stock return from July of year t+1 to June of year t+2 (July of year t-1 to June of year t); $\Delta CR_{it+1} = CR_{it+1} - CR_{it-1}$ and CR_{it+1} (CR_{it-1}) is continuous component of stock return from July of year t+1 to June of year t+2 (July of year t-1 to June of year t). To avoid bias in measuring return changes, we impose the additional requirement that the stock price must be no less than $5 at the end of June of both year $t-1$ and year t. The results are reported in Table XII. We find that small, value, and illiquid stocks have higher ΔTR and ΔCR than large, growth, and liquid stocks. This is completely the opposite of the prediction of the hypothesis.

Finally, we note that not all stocks experience jumps and that for those with jumps, the magnitude of jumps varies. A further implication of the hypothesis of risk change is that within small firms, value firms, and low liquidity firms, firms with larger jumps should have larger reduction in expected return. We test this additional prediction by performing Fama-MacBeth regressions specified in (5) within each stock quintile formed on one of the firm characteristics. The change of realized stock return is measured as the difference between the 12-month period after the month of jump and the 12-month period prior to the month of jump. We find that contrary to the prediction, jumps are positively rather than negatively correlated with changes in the total return and continuous return component. For brevity, the results are not tabulated. Overall, the evidence does not support the hypothesis that dramatic risk exposure change is the cause of predictable jumps.

VI. Concluding Remarks

Jumps are large changes in stock prices in reaction to unexpected information or liquidity shocks and occur infrequently over a small number of days. They are unexpected in nature and risks themselves, rather than a form of compensation for risks. Under both continuous and discrete time framework, compensation for risk factors or the risk premium effect is an expected component. Following this insight, we evaluate risk-based explanations of stock return predictability. The key finding of our study is that the size, the illiquidity, and to some extent the value effects, are realized in the form of jumps. We further show that the result cannot be fully reconciled with the martingale restriction of jumps, the effect of jump risk premium and investor preference for skewness, or discontinuities in expected returns. The evidence presents a clear challenge for risk-based explanations of return predictability. Nevertheless, we acknowledge that any inference on market efficiency is inevitably subject to the joint-hypothesis problem. There is a possibility that sophisticated rational asset pricing models may emerge in the future, offering predictions consistent with the findings in this paper.

Beside the issue of return predictability, our study also documents an intriguing pattern to which none of existing asset pricing theories, rational or behavior, offers a satisfactory explanation. That is, there are predominantly positive jumps in individual stock prices, in contrast to the prevalence of negative jumps at the aggregate market level. In particular, we find that small, value, illiquid stocks, as well as past losers, tend to have more positive jumps. Given our analysis, such pattern is unlikely due to sudden large shocks to risk exposure, firms' financial leverage or growth options. Then, for rational theories, the question is – what types of cash flow processes and investor expectations can give rise to the frequently positive jumps? And for the behavioral camp – what cognitive or preferential biases by investors lead to large positive surprises? The issue is important, because jumps are essential for explaining the departure of stock return from normality, and may have significant impact on investment decisions. There is an even more important implication from an asset pricing point of view – any answers to the above questions will help us to understand whether the relation between jumps and return predictability is a rational phenomenon or evidence against market efficiency.

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Appendix A: Simulations

We perform simulations to assess the performance of jump return estimation. The simulation is based on the following stock return model with stochastic volatility and random jumps:

$$
\begin{aligned}
dS_t/S_t &= \mu dt + \sqrt{V_t} dW_t^s + (\exp J_t - 1) dq_t(\lambda), \\
dV_t &= \beta(\alpha - V_t) dt + \sigma \sqrt{V_t} dW_t^v,
\end{aligned} \tag{9}
$$

where $dW_t^s dW_t^v = \rho dt$, $J_t \sim$ iid $\mathcal{N}(\mu_J, \sigma_J)$, and $dq_t(\lambda) \sim$ iid Poisson (λdt).

Model parameter values: We compute cross-sectional statistics of stocks in our sample, and use these statistics as guidance in setting the benchmark and alternative parameter values. For the benchmark, we have

- Benchmark: $\mu = 0.00032, \alpha = 0.02, \beta = 0.10, \sigma = 0.05, \rho = 0.00$.

These parameter values correspond to annualized 8% return and 32% standard deviation for an average stock. Daily return variance has a first order autocorrelation of 0.90, and a standard deviation of 0.016. There is no correlation between return and stochastic variance. To account for variations in the mean reversion of return variance, variance of variance, and correlation between return and variance, we also consider the following alternative sets of parameter values:

- Alternative I: $\mu = 0.00032, \alpha = 0.02, \beta = 0.05, \sigma = 0.05, \rho = 0.00$.
- Alternative II: $\mu = 0.00032, \alpha = 0.02, \beta = 0.20, \sigma = 0.05, \rho = 0.00$.
- Alternative III: $\mu = 0.00032, \alpha = 0.02, \beta = 0.10, \sigma = 0.025, \rho = 0.00$.
- Alternative IV: $\mu = 0.00032, \alpha = 0.02, \beta = 0.10, \sigma = 0.10, \rho = 0.00$.
- Alternative V: $\mu = 0.00032, \alpha = 0.02, \beta = 0.10, \sigma = 0.05, \rho = 0.50$.
- Alternative VI: $\mu = 0.00032, \alpha = 0.02, \beta = 0.10, \sigma = 0.05, \rho = -0.50$.

Sample path simulation: We simulate 10-minute intra-day returns for six and half hours a day over 12 years (assuming 250 trading days per year), with first two years data discarded to avoid any start-up effect. The path simulation is based on the Euler scheme of the continuous-time model. From simulated stock prices, 2,500 daily returns (10 years) are observed.

Jump returns: The jump intensity of the Poisson process is set equal to 2, which is close to the number of jumps we identified per year for an average stock. Once a jump occurs based on the random draw from the Poisson distribution, a jump is drawn from the set of empirically identified daily jumps (at 1% critical level). This way, the jump size would have the same distribution as those in our empirical analysis. The jump return is then added to simulated returns from the SV model. To further account for jump characteristics of different stocks, we also focus on jumps of the following two subsamples: stocks in the highest SIZE tercile and stocks in the lowest SIZE tercile.

Market microstructure noise: In addition, we also add an additional market microstructure noise term ($\epsilon_t \sim N(0, \sigma_M^2)$) to the simulated log asset prices. Thus, the noise of the return process follows a moving average process with standard deviation $(2\sigma_M^2)^{1/2}$ which we set as 10% of the standard deviation of true returns.

Summary of results: Jump tests are performed in each quarter on daily returns. The critical level of jump test is 1%, and we perform 15,000 replications. Since the simulations in Jiang and Oomen (2007) have examined the size and power properties, the simulations here focus on the performance of jump return estimates. We compare the estimated jump size with the true jump return in the return process. When there is no jump identified for a period, the estimated jump size is set as zero for that period. Similarly, when a period without actual jumps is misidentified as having jumps, the true jump size is set as zero in calculating the performance statistics below.

Panels 1 and 2 of Table A report the average of errors ($\hat{r}_J - r_J$) and absolute errors ($|\hat{r}_J - r_J|$) of estimated jump returns. The results show that jump estimates based on both methods have reasonable performance, and tend to slightly underestimate jump size. The results confirm the robust performance of our jump return estimation. One observation relevant to our study is that while the jump test does not have perfect power, it has lesser effect on the accuracy of jump return estimation. This is because in many cases where the jump test fails to detect jumps (lack of power), the jumps tend to small and often have offsetting sizes (thus less material effect on jump return estimation). To further ensure the reliability of the simulation results, we also simulate stock return under an alternative specification of the SV process where the log stochastic volatility is specified as an O-U process. The alternative specification of the volatility process has little impact on the performance of jump estimation.

Table A: Performance of Jump Return Estimates

Panel A: Average errors of estimated jump returns ($\times 10^{-2}$)

	Different Sets of Parameter Values						
Jumps	Benchmark	Alter-I	Alter-II	Alter-III	Alter-IV	Alter-V	Alter-VI
All Stocks	-0.24	-0.27	-0.26	-0.26	-0.30	-0.32	-0.28
Large Stocks	-0.18	-0.19	-0.19	-0.17	-0.23	-0.21	-0.19
Small Stocks	-0.32	-0.34	-0.33	-0.30	-0.39	-0.36	-0.33

Panel B: Average absolute errors of estimated jump returns ($\times 10^{-2}$)

	Different Sets of Parameter Values						
Jumps	Benchmark	Alter-I	Alter-II	Alter-III	Alter-IV	Alter-V	Alter-VI
All Stocks	0.85	0.86	0.84	0.77	0.90	0.92	0.85
Large Stocks	0.76	0.78	0.79	0.75	0.83	0.77	0.76
Small Stocks	0.92	0.99	0.98	0.94	1.02	1.00	0.95

Appendix B: Return Skewness Generated by Pure Jumps and Pure Stochastic Volatility Models

In this section, we illustrate the range of skewness of stock returns that can be generated from a stock return model with either stochastic volatility (SV) or random jump. The model we use is specified in (9). When there is no jump ($\lambda = 0$), the third and fourth moments of asset return can be derived as:

$$\begin{aligned} E[(r_t - \mu)^3] &= \frac{3}{\beta^2}(e^{-\beta} + \beta - 1)\alpha\sigma\rho \\ E[(r_t - \mu)^4] &= 3\alpha^2 + \frac{3}{\beta^3}(e^{-\beta} + \beta - 1 + 4((2+\beta)e^{-\beta} + \beta - 2)\rho^2)\alpha\sigma^2 \end{aligned}$$

where $r_t = \ln S_t - \ln S_{t-1}$, and the second moment of return is given by $E[(r_t - \mu)^2] = \alpha$. Under the random jump model, the third and fourth moments of asset return can be derived as:

$$\begin{aligned} E[(r_t - \mu)^3] &= \lambda\mu_J(3\sigma_J^2 + \mu_J^2) \\ E[(r_t - \mu)^4] &= \lambda(3\sigma_J^4 + 6\sigma_J^2\mu_J^2 + \mu_J^4) \end{aligned}$$

where the second moment of return is given by $E[(r_t - \mu)^2] = \lambda(\sigma_J^2 + \mu_J^2)$.

Panel 1 of Table B reports the cross-sectional distribution of the skewness of daily log returns for individual stocks in our sample. The cross-sectional mean and median of skewness are positive, at 0.18 and 0.19 respectively. Panel 2 illustrates the skewness generated by the pure jump model under constant volatility, with $\sigma_J = 0.126$ (or annualized 20% standard deviation of jump size). The values of μ_J and λ are assigned with different values so that the total return volatility is fixed at 0.036. Increasing the value of σ_J will further increase the range of skewness. In Panel 3, the skewness is generated by a pure stochastic volatility model without jumps. We use the benchmark parameter values in Appendix A, but let the value of ρ change from -1 to 1.

As the table shows, it is very difficult for the stochastic volatility model to generate sufficiently high return skewness that can match observed empirical distribution of skewness. On the other hand, a model with jump and constant-volatility can easily generate skewness comparable with the observed empirical skewness.

Table B: Stock Return Skewness

Panel 1: Empirical cross-sectional distribution of skewness of daily log returns											
Cross-sectional distribution					5%	25%	Mean	Median	75%	95%	StDev
					-1.17	-0.13	0.18	0.19	0.52	1.47	1.04
Panel 2: Skewness generated by pure jump model											
Jump size μ_J	-0.40	-0.32	-0.24	-0.16	-0.08	0.00	0.08	0.16	0.24	0.32	0.40
Frequency λ	0.20	0.30	0.48	0.86	1.61	2.26	1.61	0.86	0.48	0.30	0.20
Skewness	-2.48	-2.13	-1.81	-1.48	-1.02	0.00	1.02	1.48	1.81	2.13	2.48
Panel 3: Skewness generated by stochastic volatility model											
Correlation ρ	-1.0	-0.8	-0.6	-0.4	-0.2	0.0	0.2	0.4	0.6	0.8	1.0
Skewness	-0.14	-0.11	-0.08	-0.05	-0.02	0.0	0.02	0.05	0.08	0.11	0.14

Appendix C: Other Market Anomalies

This table provides results on returns, jump returns, and continuous returns to quintile portfolios formed on an expanded set of return-predictive variables. The 20 variables fall into one of the following nine categories: size, value, momentum, earnings quality, growth, financing, intangible investments, profitability, and liquidity. They are signed so that the higher the value the higher the predicted returns. Details on variable definition and construction are available upon request. In each year t we sort stocks into equal-weighted quintile portfolios based one of the 20 variables. The portfolios are held without rebalancing from July of year t to June of year $t+1$. For each quintile, we compute the averages of returns, jump returns, and continuous returns across all stocks within the portfolio. We then calculate the differences of these statistics between the top and bottom quintiles, and finally, take the time series averages of the differences and report them in the table. Inside the parentheses are t-statistics. The sample holding period is from July 1974 to June 2005.

variable	variable explanation	total return	jump return	continuous return
size				
-SIZE	market cap	5.52 (1.85)	6.38 (5.17)	-0.86 (-0.26)
value				
BM	book to market ratio	11.20 (3.21)	2.86 (4.20)	8.34 (2.53)
EP	earnings to price ratio	10.43 (2.77)	-4.31 (-3.31)	14.74 (4.50)
OPCFP	operating cashflow to price	14.33 (2.74)	-4.60 (-2.27)	18.93 (4.09)
momentum				
MOM	price momentum	6.58 (2.09)	-4.58 (-5.47)	11.15 (3.73)
earnings quality				
-ACC	accruals to total assets (TA)	5.59 (3.61)	2.42 (6.47)	3.17 (2.20)
-NOA	net operating assets to TA	7.66 (3.07)	3.79 (4.35)	3.87 (2.05)
growth				
-CAPEX	capital expenditure to TA	4.75 (3.39)	2.63 (6.92)	2.11 (1.54)
-AG	annual asset growth rate	9.94 (4.47)	3.80 (7.99)	6.14 (2.64)
-EMPG	annual employee growth rate	5.03 (2.60)	2.44 (5.35)	2.60 (1.35)
-SG	annual sales growth rate	4.54 (2.19)	2.50 (5.95)	2.03 (1.01)
financing				
-NS	net share issues	12.93 (5.45)	0.31 (0.43)	12.63 (5.33)
-EXTF	total equity and debt financing to TA	10.39 (3.57)	-1.05 (-1.43)	11.43 (3.83)
intangible investments				
R&D	R&D expenditure to marketcap	12.25 (2.96)	7.37 (5.54)	4.88 (1.59)
ADV	advertising expenditure to marketcap	9.82 (2.40)	3.42 (4.03)	6.40 (1.71)
SGA	SGA expense to marketcap	12.96 (4.52)	4.99 (10.25)	7.97 (2.87)
profitability				
ROI	return on invested capital	6.78 (2.72)	-6.49 (-7.19)	13.27 (5.90)
liquidity				
-TURN	turnover	6.74 (2.14)	-3.66 (-3.02)	10.40 (4.10)
ILLIQ	Amihud illiquidity ratio	6.94 (2.35)	7.80 (10.45)	-0.85 (-0.35)
-DTURN	dollar turnover	7.72 (2.68)	3.93 (5.63)	3.79 (1.54)

Table I
Summary Statistics of Stock Price Jumps

This table reports the cross-sectional summary statistics of identified jumps of individual stock prices. From July 1927 to June 2005, we identify jumps using the variance swap approach, based on daily returns in each quarter at the 1% critical level. The sample includes all non-financial common stocks with end-of-June price no less than $5 and at least 44 daily return observations during the jump identification quarter. Jump frequency (number of jumps per year) is calculated for each stock as the ratio of the number of identified jumps to the total number of years the stock is in the sample. Jump size is the average jump return (expressed in log return form) for each stock in the sample. Jump frequency and size are also calculated for positive and negative jumps separately. We report the following cross-sectional statistics for the distributions of jump frequency and jump size for the entire sample period and two subperiods: 5th percentile, 1st quartile, mean, median, 3rd quartile, 95th percentile, and standard deviation.

	5%	25%	Mean	Median	75%	95%	StDev
Panel A: Sample period 1927/07-2005/06							
Number of jumps per year	0.00	1.00	2.07	2.00	3.00	4.50	1.52
Number of positive jumps per year	0.00	0.50	1.37	1.33	2.00	3.00	1.08
Number of negative jumps per year	0.00	0.09	0.71	0.56	1.00	2.00	0.77
Jump size	-12.62	0.37	2.51	3.05	6.10	15.24	10.80
Positive jump size	5.26	7.90	12.74	10.69	14.85	27.17	8.13
Negative jump size	-35.45	-18.44	-15.25	-11.97	-8.25	-5.21	11.47
Panel B: Sample period 1927/07-1962/06							
Number of jumps per year	0.00	1.38	2.04	2.00	2.60	3.78	1.10
Number of positive jumps per year	0.00	0.96	1.47	1.42	1.93	2.92	0.89
Number of negative jumps per year	0.00	0.29	0.57	0.52	0.76	1.25	0.44
Jump size	-0.94	1.44	2.73	2.63	4.09	7.29	4.34
Positive jump size	3.56	5.25	7.50	6.59	8.37	14.09	4.29
Negative jump size	-19.24	-10.05	-8.67	-7.23	-5.39	-3.60	6.14
Panel C: Sample period 1962/07-2005/06							
Number of jumps per year	0.00	1.00	2.09	2.00	3.00	4.50	1.54
Number of positive jumps per year	0.00	0.50	1.38	1.33	2.00	3.13	1.09
Number of negative jumps per year	0.00	0.00	0.71	0.57	1.00	2.00	0.78
Jump size	-12.81	0.29	2.52	3.07	6.22	15.39	10.92
Positive jump size	5.22	8.00	12.83	10.80	14.93	27.25	8.17
Negative jump size	-35.67	-18.59	-15.38	-12.15	-8.34	-5.08	11.55

Table II
Summary Statistics of Return-Predictive Variables

Panel A reports the cross-sectional summary statistics of the return-predictive variables: log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM, in percentage points), net stock issues (NS), and the Amihud (2002) illiquidity ratio (*illiq ratio*, pre-multiplied by 10^6). We report the number of stocks (N) with valid observations for each variable, the cross-sectional mean, median, standard deviation, and the 5th, 25th, 75th, and 95th percentiles for five selected years: 1927, 1940, 1960, 1980, and 2004. The *illiq ratio* are reported for NASDAQ stocks (available after 1982) and for NYSE-AMEX stocks separately in the year of 2004. Panel B reports the correlations of return-predictive variables, which are computed each year and then averaged over time for the entire sample period (1927-2004) and for two subperiods (1927-1961 and 1962-2004). Since trading volume is defined differently for NASDAQ stocks and NYSE-AMEX stocks, we compute the annual cross-sectional percentile rank of the illiquidity ratio, denoted by ILLIQ, where NASDAQ stocks and NYSE-AMEX stocks are ranked separately.

Panel A: Cross-Sectional Distribution of Return-Predictive Variables

Year	Variable	N	5%	25%	Mean	Median	75%	95%	StDev
1927	SIZE	506	7.43	8.89	9.89	9.77	10.93	12.49	1.54
	BM	431	-8.07	-7.29	-6.80	-6.85	-6.36	-5.38	0.85
	MOM	474	-37.78	-8.05	19.94	14.84	37.24	99.78	46.24
	NS	67	-3E-04	6E-04	0.19	0.08	0.28	0.92	0.33
	illiq ratio	416	0.02	0.11	1.81	0.43	1.40	9.36	4.01
1940	SIZE	566	7.53	8.48	9.56	9.35	10.40	12.37	1.47
	BM	528	-8.26	-7.43	-6.89	-6.92	-6.36	-5.40	0.89
	MOM	556	-34.21	-14.93	5.12	0.31	16.20	63.31	35.34
	NS	34	-0.01	0.00	0.13	0.01	0.10	0.76	0.42
	illiq ratio	496	0.13	0.82	5.22	2.31	5.30	17.82	13.72
1960	SIZE	1008	8.96	10.13	11.21	11.09	12.13	13.74	1.49
	BM	959	-7.82	-6.86	-3.25	-1.14	-0.38	0.32	3.27
	MOM	982	-34.23	-17.19	0.83	-4.99	14.35	51.41	29.52
	NS	670	-0.01	0.00	0.03	0.01	0.04	0.20	0.11
	illiq ratio	972	0.03	0.13	0.88	0.36	0.94	3.41	1.66
1980	SIZE	2785	8.74	9.85	11.14	10.93	12.31	14.08	1.67
	BM	2574	-1.54	-0.56	-0.20	-0.01	0.39	0.85	1.07
	MOM	2714	-28.48	-3.28	26.97	13.93	42.49	118.23	54.61
	NS	2315	-0.04	0.00	0.03	0.01	0.03	0.18	0.11
	illiq ratio	1711	0.01	0.04	0.91	0.19	0.77	4.36	2.00
2004	SIZE	3208	10.71	12.15	13.31	13.20	14.36	16.36	1.70
	BM	2976	-2.19	-1.29	-0.86	-0.74	-0.32	0.27	0.85
	MOM	3089	-19.71	11.78	57.10	34.75	74.12	199.89	90.78
	NS	2978	-0.05	9E-04	0.07	0.01	0.04	0.29	0.38
	illiq ratio (NYAM)	1426	1E-04	6E-04	0.15	3E-03	0.02	0.73	0.71
	illiq ratio (NASD)	1674	4E-04	3E-03	0.46	0.02	0.13	2.36	1.78

Panel B: Cross-Sectional Correlations of Return-Predictive Variables

Sample period		SIZE	BM	MOM	NS	ILLIQ
1927-2004	SIZE	1.00				
	BM	-0.15	1.00			
	MOM	0.05	-0.04	1.00		
	NS	-0.05	-0.07	-0.02	1.00	
	ILLIQ	-0.84	0.19	0.02	0.03	1.00
1927-1961	SIZE	1.00				
	BM	-0.19	1.00			
	MOM	0.08	-0.02	1.00		
	NS	-0.08	-0.03	-0.03	1.00	
	ILLIQ	-0.85	0.16	-0.01	0.10	1.00
1962-2004	SIZE	1.00				
	BM	-0.11	1.00			
	MOM	0.02	-0.07	1.00		
	NS	-0.02	-0.11	-0.01	1.00	
	ILLIQ	-0.83	0.21	0.05	-0.03	1.00

Table III
Average Returns across Stock Quintiles

From 1927 to 2004, in June of each year t we sort stocks to form equal-weighted quintile portfolios based on one of the five return-predictive variables: SIZE, BM, MOM, NS, and ILLIQ. The portfolios are held for the next 12-month from July of year t to June of year t+1. This table reports the average number of stocks (N) in each quintile portfolio, the average annual return of each portfolio (in percentage points), the average return spreads between top and bottom quintiles, and the time series t-statistics for the return spreads. The results are reported for the entire holding period (1927/07-2005/06) and two subperiods (1927/07-1962/06 and 1962/07-2005/06).

Quintile	SIZE	BM	MOM	NS	ILLIQ
Panel A: Holding period 1927/07-2005/06					
Q1	18.81	10.81	14.46	19.08	12.05
Q2	16.08	14.47	14.99	16.20	13.10
Q3	15.96	15.91	16.30	16.96	15.48
Q4	14.37	18.05	16.85	13.77	17.56
Q5	13.09	20.74	17.37	11.96	19.94
Q5-Q1	-5.71	9.92	2.90	-7.12	7.89
t-Stat	(-2.55)	(3.86)	(0.97)	(-4.26)	(3.61)
N	385	343	351	275	336
Panel B: Holding period 1927/07-1962/06					
Q1	18.25	11.44	17.36	17.59	12.73
Q2	16.44	15.18	15.06	15.36	14.13
Q3	16.95	15.89	15.71	17.17	16.54
Q4	14.51	18.43	16.37	13.09	18.51
Q5	13.44	21.17	16.30	15.42	19.65
Q5-Q1	-4.81	9.73	-1.06	-2.18	6.92
t-Stat	(-1.36)	(2.04)	(-0.18)	(-0.82)	(2.03)
N	148	138	141	44	134
Panel C: Holding period 1962/07-2005/06					
Q1	19.26	10.31	12.11	20.29	11.50
Q2	15.78	13.89	14.94	16.88	12.26
Q3	15.16	15.92	16.78	16.80	14.61
Q4	14.27	17.74	17.24	14.33	16.79
Q5	12.81	20.39	18.24	9.15	20.17
Q5-Q1	-6.45	10.08	6.13	-11.14	8.67
t-Stat	(-2.22)	(3.79)	(2.53)	(-5.73)	(3.03)
N	578	510	522	463	500

Table IV
Jump and Continuous Return Components across Stock Quintiles

This table reports time series averages of jump returns (JR) and continuous returns (CR) for each quintile portfolio sorted on each of the five predictive variables: SIZE, BM, MOM, NS, and ILLIQ. The spreads of jump return component and continuous return component between top and bottom quintiles, as well as their time series t-statistics, are also reported.

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	JR	CR	JR	CR	JR	CR	JR	CR	JR	CR
Panel A: Holding period 1927/07-2005/06										
Q1	12.58	6.22	7.55	3.27	12.29	2.18	8.55	10.54	5.30	6.75
Q2	11.30	4.77	8.40	6.07	8.74	6.25	8.94	7.26	7.40	5.70
Q3	9.36	6.61	8.50	7.40	7.66	8.64	8.51	8.46	9.92	5.56
Q4	7.15	7.23	8.92	9.13	7.39	9.46	9.19	4.58	11.98	5.58
Q5	4.52	8.58	11.13	9.61	9.04	8.33	9.75	2.22	14.84	5.09
Q5-Q1	-8.07	2.35	3.58	6.34	-3.25	6.15	1.20	-8.32	9.55	-1.66
t-Stat	(-8.06)	(1.08)	(6.07)	(2.78)	(-4.03)	(2.32)	(1.26)	(-5.22)	(10.99)	(-0.94)
Panel B: Holding period 1927/07-1962/06										
Q1	10.11	8.14	6.29	5.15	9.90	7.46	6.56	11.03	5.40	7.33
Q2	8.96	7.47	6.94	8.24	7.75	7.31	7.95	7.40	6.49	7.64
Q3	7.74	9.21	7.27	8.62	6.88	8.83	6.96	10.21	7.88	8.66
Q4	6.41	8.10	7.43	11.00	6.30	10.07	8.40	4.68	9.14	9.38
Q5	4.71	8.73	9.93	11.24	7.80	8.50	8.89	6.52	12.16	7.49
Q5-Q1	-5.40	0.59	3.64	6.09	-2.10	1.04	2.33	-4.51	6.76	0.16
t-Stat	(-6.48)	(0.17)	(3.62)	(1.50)	(-1.66)	(0.20)	(1.21)	(-1.79)	(7.86)	(0.05)
Panel C: Holding period 1962/07-2005/06										
Q1	14.60	4.66	8.58	1.73	14.23	-2.12	10.16	10.13	5.21	6.29
Q2	13.21	2.58	9.58	4.31	9.55	5.39	9.75	7.14	8.14	4.12
Q3	10.67	4.49	9.51	6.41	8.29	8.48	9.77	7.03	11.58	3.03
Q4	7.75	6.51	10.13	7.61	8.28	8.96	9.83	4.50	14.30	2.49
Q5	4.36	8.45	12.11	8.28	10.04	8.19	10.44	-1.29	17.03	3.14
Q5-Q1	-10.24	3.79	3.53	6.55	-4.19	10.31	0.28	-11.43	11.82	-3.15
t-Stat	(-6.32)	(1.36)	(5.05)	(2.58)	(-4.07)	(4.59)	(0.38)	(-5.87)	(8.94)	(-1.49)

Table V
Returns across Stock Quintiles: Stock with Jumps vs. Stocks without Jumps

Stocks are divided into two subgroups: those with jumps (With Jump) and those without jumps (No Jump). This table reports average returns of quintile portfolios in each of the subgroups. The quintile portfolios in each subgroup are formed on each of the five predictive variables: SIZE, BM, MOM, NS, and ILLIQ. The average return spreads between top and bottom quintiles, and their time series t-statistics, are also reported. Jumps are identified at the 1% critical level.

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	With Jump	No Jump	With Jump	No Jump	With Jump	No Jump	With Jump	No Jump	With Jump	No Jump
Panel A: Holding period 1927/07-2005/06										
1	24.48	9.38	11.81	8.31	17.22	7.23	24.31	15.29	12.86	10.00
2	19.68	9.35	16.78	9.44	18.07	9.71	18.11	11.66	14.59	9.53
3	18.17	9.62	19.13	9.36	18.76	11.33	19.21	9.21	18.05	8.54
4	16.04	10.74	20.72	11.50	19.14	11.55	16.71	8.67	20.81	8.74
5	14.27	10.10	25.21	13.25	20.39	11.67	12.75	8.78	24.80	8.18
Q5-Q1	-10.21	0.72	13.41	4.94	3.18	4.44	-11.56	-6.51	11.94	-1.83
t-Stat	-(4.23)	(0.31)	(4.60)	(2.01)	(1.07)	(1.97)	-(3.22)	-(2.57)	(5.20)	-(0.86)
Panel B: Holding period 1927/07-1962/06										
1	24.16	8.48	13.10	7.51	19.62	9.76	26.75	14.78	14.01	9.13
2	20.86	9.70	17.79	8.75	18.92	8.67	16.68	11.64	15.68	10.06
3	19.52	8.82	19.91	8.02	18.13	10.34	19.21	5.23	18.96	8.29
4	16.42	9.12	20.87	10.74	18.93	10.26	17.10	6.36	21.24	9.78
5	15.30	8.68	26.90	12.82	20.90	7.73	15.12	13.37	24.12	10.07
Q5-Q1	-8.86	0.21	13.80	5.31	1.29	-2.03	-11.63	-1.40	10.11	0.94
t-Stat	(-2.17)	(0.06)	(2.46)	(1.19)	(0.22)	(-0.53)	(-1.52)	(-0.28)	(2.72)	(0.25)
Panel C: Holding period 1962/07-2005/06										
1	24.73	10.12	10.75	8.96	15.26	5.16	22.33	15.71	11.93	10.71
2	18.73	9.06	15.95	10.00	17.38	10.55	19.28	11.68	13.70	9.11
3	17.06	10.28	18.50	10.46	19.28	12.13	19.20	12.37	17.31	8.73
4	15.72	12.05	20.59	12.13	19.30	12.60	16.40	10.56	20.46	7.89
5	13.43	11.26	23.84	13.60	19.98	14.88	10.83	5.16	25.36	6.63
Q5-Q1	-11.31	1.14	13.09	4.64	4.71	9.71	-11.50	-10.55	13.43	-4.08
t-Stat	-(3.91)	(0.39)	(4.77)	(1.77)	(1.93)	(4.03)	-(5.60)	-(5.43)	(4.66)	-(1.82)

Table VI
Return Spreads between the Top and Bottom Value-Weighted Stock Quintiles

This table reports the spreads of total stock return (TR), the spreads of the jump return component (JR) and the spreads of the continuous return component (CR) between the top and bottom value-weighted quintile portfolios. The quintile portfolios are formed on each of the five predictive variables: SIZE, BM, MOM, NS, and ILLIQ. The time series t-statistics of return spreads are also reported. Jumps are identified at the 1% critical level.

Quintile Spreads of Returns (Q5-Q1)	SIZE	BM	MOM	NS	ILLIQ
Panel A: Holding period 1927/07-2005/06					
TR	-5.85	5.68	3.94	-5.97	7.08
t-Stat	(-2.25)	(2.34)	(1.20)	(-3.22)	(2.74)
JR	-9.24	4.07	-3.77	0.26	9.14
t-Stat	(-9.30)	(3.94)	(-4.45)	(0.29)	(10.03)
CR	3.39	1.61	7.71	-6.24	-2.07
t-Stat	(1.37)	(0.80)	(2.65)	(-3.56)	(-1.04)
Panel B: Holding period 1927/07-1962/06					
TR	-4.85	6.36	0.04	-4.81	7.20
t-Stat	(-1.20)	(1.47)	(0.01)	(-1.39)	(1.59)
JR	-6.05	4.28	-3.11	1.13	7.49
t-Stat	(-8.24)	(1.93)	(-2.27)	(0.58)	(5.73)
CR	1.21	2.08	3.15	-5.94	-0.29
t-Stat	(0.31)	(0.64)	(0.57)	(-1.77)	(-0.08)
Panel C: Holding period 1962/07-2005/06					
TR	-6.67	5.13	7.11	-6.92	6.98
t-Stat	(-1.96)	(1.91)	(2.32)	(-3.69)	(2.37)
JR	-11.84	3.89	-4.30	-0.44	10.49
t-Stat	(-7.38)	(7.32)	(-4.05)	(-0.84)	(8.45)
CR	5.17	1.24	11.42	-6.48	-3.52
t-Stat	(1.60)	(0.49)	(4.25)	(-3.89)	(-1.56)

Table VII

Quintile Spreads of Total Returns, Earnings Announcement Returns, Jump Returns, and Continuous Returns

This table reports the spreads of total stock return (TR), earnings announcement return (EAR), non-earnings announcement return (Non-EAR), jump return component (JR), and continuous return component (CR) between the top and bottom quintile portfolios sorted on one of the five predictive variables: SIZE, BM, MOM, NS, and ILLIQ. Earnings announcement returns (EAR) are aggregated stock returns during the four trading-day window starting from two days prior to earnings announcement dates, where announcement dates are based on Compustat quarterly data. Non-announcement returns (Non-EAR) is the difference between total stock return during the 12-month holding period and EAR. The time series t-statistics of return spreads are also reported. The holding period is from July 1974 to June 2005 due to availability of earnings announcement dates.

Quintile Spreads of Returns (Q5-Q1)	SIZE	BM	MOM	NS	ILLIQ
TR	-5.58	11.09	6.22	-12.52	8.02
t-Stat	(-1.97)	(3.14)	(2.07)	(-4.95)	(2.59)
EAR	-0.33	2.22	-0.07	-2.10	1.46
t-Stat	(-1.41)	(5.62)	(-0.21)	(-5.28)	(4.07)
Non-EAR	-5.25	8.87	6.29	-10.41	6.56
t-Stat	(-1.92)	(2.72)	(2.23)	(-4.66)	(2.25)
JR	-12.00	3.16	-3.76	-0.37	12.68
t-Stat	(-10.72)	(4.20)	(-4.25)	(-0.38)	(11.76)
CR	6.43	7.93	9.96	-12.15	-4.68
t-Stat	(2.49)	(2.51)	(3.47)	(-4.80)	(-1.98)

Table VIII
Average Returns across Stock Quintiles: Controlling for the Jump Effect

This table reports average total return (TR) and continuous return component (CR) of stock quintiles after controlling for the jump effect. In each year t, stocks are sorted into five groups based on jump returns during July of year t to June of year t+1. Within each jump-sorted group, we further sort stocks into quintiles based on one of the five firm characteristics measured during year t: SIZE, BM, MOM, NS, and ILLIQ. Then, stocks with the same firm characteristic rank across all the jump-sorted groups are combined into a characteristic group. We compute the average returns of stocks in each characteristic group, as well as the average return spreads between the top and bottom characteristic groups. The time series t-statistics for the return spreads are also reported.

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	TR	CR	TR	CR	TR	CR	TR	CR	TR	CR
Panel A: Holding period 1927/07-2005/06										
Q1	16.84	7.17	12.00	3.25	12.52	3.19	17.43	9.20	14.41	5.19
Q2	14.96	5.67	15.00	6.07	15.50	6.48	17.46	8.46	14.87	5.37
Q3	15.51	6.56	15.89	7.08	16.89	7.97	15.27	5.89	15.67	5.68
Q4	15.78	7.05	17.40	8.68	17.42	8.68	14.59	5.56	16.34	6.26
Q5	15.26	6.99	19.66	10.38	17.64	8.54	12.87	3.99	16.84	6.17
Q5-Q1	-1.58	-0.18	7.66	7.14	5.12	5.34	-4.56	-5.20	2.43	0.99
t-Stat	(-0.79)	(-0.09)	(3.18)	(2.99)	(2.09)	(2.22)	(-2.65)	(-3.05)	(1.36)	(0.57)
Panel B: Holding period 1927/07-1962/06										
Q1	17.36	9.48	12.50	5.17	15.75	7.88	14.55	8.15	14.43	6.70
Q2	15.75	7.89	15.91	8.25	15.63	7.90	18.59	10.68	15.24	7.32
Q3	16.20	8.74	15.67	8.17	16.36	8.61	13.47	4.98	16.58	8.34
Q4	15.43	7.84	17.43	10.18	16.47	9.03	14.63	6.81	17.74	9.40
Q5	14.91	7.78	20.57	12.46	16.64	8.80	16.56	9.34	17.52	8.67
Q5-Q1	-2.45	-1.70	8.07	7.29	0.89	0.92	2.01	1.19	3.09	1.97
t-Stat	(-0.72)	(-0.50)	(1.75)	(1.61)	(0.19)	(0.20)	(0.68)	(0.42)	(1.00)	(0.66)
Panel C: Holding period 1962/07-2005/06										
Q1	16.42	5.29	11.60	1.69	9.90	-0.62	19.77	10.05	14.38	3.95
Q2	14.32	3.87	14.26	4.30	15.40	5.33	16.53	6.66	14.56	3.78
Q3	14.94	4.79	16.07	6.19	17.33	7.45	16.73	6.64	14.93	3.52
Q4	16.06	6.42	17.38	7.46	18.19	8.40	14.56	4.54	15.21	3.70
Q5	15.55	6.34	18.92	8.69	18.47	8.32	9.87	-0.36	16.28	4.15
Q5-Q1	-0.87	1.06	7.33	7.01	8.57	8.94	-9.90	-10.40	1.90	0.19
t-Stat	(-0.37)	(0.45)	(3.23)	(3.01)	(4.07)	(4.26)	(-6.22)	(-6.02)	(0.92)	(0.09)

Table IX
Estimates of Expected Jumps and Expected Returns across Stock Quintiles

This table reports the average estimates of expected jumps (E(JR)) and expected return (E(R)) for stock quintiles sorted on one of the five firm characteristics: SIZE, BM, MOM, NS, and ILLIQ. Assuming expected jump is a linear function of realized jumps, its estimate is obtained from cross-sectional regression of continuous returns (CR) against jump returns (JR). Estimate of expected return (E(R)) is the continuous return component after adjusting for expected jumps.

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	E(JR)	E(R)	E(JR)	E(R)	E(JR)	E(R)	E(JR)	E(R)	E(JR)	E(R)
Panel A: Holding period 1927/07-2005/06										
Q1	10.29	16.51	8.57	11.83	10.20	12.38	8.70	19.24	7.78	14.54
Q2	9.74	14.52	8.72	14.79	8.93	15.18	8.76	16.01	8.31	14.01
Q3	9.04	15.65	8.78	16.18	8.50	17.13	8.76	17.22	9.47	15.03
Q4	8.29	15.52	9.04	18.17	8.46	17.92	9.02	13.60	9.82	15.40
Q5	7.51	16.09	9.58	19.19	8.91	17.23	9.24	11.45	10.82	15.91
Q5-Q1	-2.78	-0.42	1.02	7.36	-1.30	4.85	0.54	-7.78	3.03	1.37
t-Stat	(-5.69)	(-0.21)	(3.65)	(3.28)	(-3.41)	(1.84)	(1.24)	(-4.78)	(7.27)	(0.78)
Panel B: Holding period 1927/07-1962/06										
Q1	8.41	16.56	7.27	12.42	8.34	15.80	7.04	18.07	7.08	14.40
Q2	7.93	15.40	7.20	15.44	7.64	14.95	7.33	14.73	6.99	14.63
Q3	7.58	16.79	7.40	16.02	7.30	16.12	7.32	17.53	7.77	16.43
Q4	7.06	15.16	7.73	18.72	7.30	17.37	7.76	12.44	7.61	16.99
Q5	6.94	15.67	8.12	19.36	7.57	16.06	7.84	14.36	8.70	16.19
Q5-Q1	-1.47	-0.88	0.85	6.94	-0.77	0.26	0.80	-3.70	1.62	1.78
t-Stat	(-3.76)	(-0.26)	(1.75)	(1.76)	(-1.36)	(0.05)	(0.92)	(-1.36)	(3.64)	(0.63)
Panel C: Holding period 1962/07-2005/06										
Q1	11.82	16.48	9.62	11.35	11.72	9.60	10.06	20.19	8.36	14.65
Q2	11.22	13.79	9.95	14.26	9.97	15.36	9.92	17.06	9.39	13.51
Q3	10.23	14.72	9.90	16.31	9.47	17.95	9.94	16.98	10.85	13.89
Q4	9.29	15.81	10.11	17.71	9.41	18.37	10.04	14.55	11.61	14.10
Q5	7.98	16.43	10.77	19.05	10.00	18.19	10.38	9.09	12.54	15.68
Q5-Q1	-3.84	-0.05	1.15	7.70	-1.72	8.59	0.32	-11.11	4.18	1.03
t-Stat	(-4.83)	(-0.02)	(3.62)	(3.04)	(-3.39)	(3.74)	(0.96)	(-6.11)	(6.80)	(0.47)

Table X
Jump Risk and Skewness across Stock Quintiles

This table reports average jump risk (JRisk) and return skewness (Skew) of individual stocks across stock quintiles. Jump risk is based on the difference between realized variance (RV) and the bi-power variation (BPV). Skewness is measured for log returns. Both jump risk and skewness are ex ante measures, based on daily returns during the 12 months prior to the portfolio holding period. The quintile portfolios are formed on each of the firm characteristics: SIZE, BM, MOM, NS, and ILLIQ. The differences of each measure between the top and bottom quintiles, as well as their time series t-statistics, are also reported.

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	JRisk	Skew	JRisk	Skew	JRisk	Skew	JRisk	Skew	JRisk	Skew
Panel A: Holding period 1927/07-2005/06										
Q1	0.06	0.37	0.03	0.15	0.04	-0.09	0.03	0.30	0.01	0.03
Q2	0.04	0.27	0.03	0.16	0.03	0.12	0.04	0.22	0.02	0.10
Q3	0.03	0.21	0.03	0.19	0.02	0.22	0.02	0.18	0.02	0.17
Q4	0.02	0.14	0.03	0.24	0.02	0.32	0.03	0.14	0.03	0.27
Q5	0.01	0.07	0.05	0.29	0.04	0.50	0.04	0.14	0.05	0.40
Q5-Q1	-0.05	-0.30	0.02	0.14	0.00	0.59	0.01	-0.16	0.03	0.37
t-Stat	(-5.16)	(-8.45)	(2.56)	(6.23)	(0.42)	(14.24)	(1.83)	(-5.76)	(7.57)	(13.01)
Panel B: Holding period 1927/07-1962/06										
Q1	0.08	0.20	0.02	0.12	0.04	-0.04	0.03	0.21	0.01	0.04
Q2	0.04	0.18	0.02	0.12	0.03	0.08	0.06	0.15	0.01	0.10
Q3	0.03	0.15	0.03	0.14	0.03	0.13	0.02	0.15	0.02	0.12
Q4	0.02	0.11	0.04	0.15	0.02	0.20	0.02	0.10	0.03	0.16
Q5	0.02	0.05	0.06	0.15	0.05	0.33	0.04	0.11	0.05	0.26
Q5-Q1	-0.06	-0.15	0.04	0.04	0.01	0.37	0.00	-0.10	0.04	0.22
t-Stat	(-2.87)	(-3.50)	(3.28)	(1.07)	(0.81)	(10.49)	(0.29)	(-1.96)	(4.50)	(5.53)
Panel C: Holding period 1962/07-2005/06										
Q1	0.05	0.51	0.04	0.18	0.04	-0.14	0.03	0.37	0.02	0.02
Q2	0.04	0.35	0.03	0.18	0.02	0.15	0.02	0.29	0.02	0.10
Q3	0.03	0.26	0.03	0.24	0.02	0.29	0.03	0.21	0.03	0.22
Q4	0.02	0.17	0.03	0.31	0.02	0.42	0.03	0.17	0.03	0.35
Q5	0.01	0.08	0.03	0.40	0.04	0.64	0.04	0.16	0.04	0.52
Q5-Q1	-0.04	-0.43	-0.01	0.22	0.00	0.77	0.01	-0.21	0.03	0.50
t-Stat	(-19.36)	(-9.04)	(-3.43)	(10.00)	(-0.70)	(13.81)	(4.35)	(-8.15)	(15.56)	(16.76)

Table XI
Return Spreads across Stock Quintiles: Controlling for Jump Risk and Skewness

We first sort stocks into five groups based on ex ante measures of either jump risk or return skewness. Within each group, we further sort stocks into quintiles based on one of the five return-predictive variables: SIZE, BM, MOM, NS, and ILLIQ. Then, stocks with the same firm characteristic rank across all the jump risk or skewness groups are combined to form equal-weighted quintile portfolios. This table reports the differences of average total stock return (TR), jump return (JR), and continuous return (CR) between the top and bottom quintile portfolios. The times series t-statistics of return spreads are also reported.

	Controlling for Jump Risk					Controlling for Skewness				
Return Spreads	SIZE	BM	MOM	NS	ILLIQ	SIZE	BM	MOM	NS	ILLIQ
Panel A: Holding period 1927/07-2005/06										
TR	-5.13	8.95	3.85	-4.53	6.88	-5.71	9.75	2.83	-8.26	7.69
t-Stat	(-3.13)	(3.72)	(1.41)	(-2.12)	(4.12)	(-2.52)	(3.83)	(1.01)	(-4.64)	(3.69)
JR	-5.15	2.91	-3.23	0.79	5.77	-7.44	3.46	-4.25	1.47	8.61
t-Stat	(-6.94)	(5.29)	(-4.98)	(0.88)	(9.23)	(-8.24)	(6.09)	(-5.68)	(1.63)	(11.15)
CR	0.02	6.04	7.07	-5.37	1.10	1.73	6.29	7.08	-9.81	-0.93
t-Stat	(0.01)	(2.89)	(2.95)	(-2.92)	(0.79)	(0.79)	(2.76)	(2.86)	(-5.05)	(-0.55)
Panel B: Holding period 1927/07-1962/06										
TR	-3.63	8.59	1.27	2.42	4.81	-5.89	9.85	-0.75	-5.23	6.46
t-Stat	(-1.51)	(1.91)	(0.24)	(0.61)	(2.06)	(-1.55)	(2.09)	(-0.14)	(-1.68)	(1.99)
JR	-2.54	2.50	-2.05	2.57	3.18	-4.89	3.59	-2.88	2.69	6.15
t-Stat	(-4.29)	(2.46)	(-1.93)	(1.37)	(4.99)	(-6.67)	(3.61)	(-2.35)	(1.48)	(7.21)
CR	-1.09	6.09	3.33	-0.26	1.63	-1.00	6.26	2.13	-8.07	0.30
t-Stat	(-0.46)	(1.61)	(0.71)	(-0.08)	(0.76)	(-0.27)	(1.53)	(0.45)	(-2.22)	(0.11)
Panel C: Holding period 1962/07-2005/06										
TR	-6.36	9.24	5.94	-10.19	8.55	-5.57	9.68	5.74	-10.73	8.69
t-Stat	(-2.83)	(3.79)	(2.55)	(-5.77)	(3.64)	(-2.02)	(3.70)	(2.49)	(-5.46)	(3.18)
JR	-7.27	3.25	-4.18	-0.66	7.89	-9.51	3.37	-5.37	0.48	10.61
t-Stat	(-6.23)	(5.71)	(-5.40)	(-1.31)	(8.83)	(-6.53)	(5.17)	(-5.97)	(0.67)	(9.34)
CR	0.92	5.99	10.12	-9.53	0.66	3.95	6.32	11.10	-11.22	-1.93
t-Stat	(0.43)	(2.67)	(4.91)	(-5.51)	(0.36)	(1.52)	(2.55)	(5.15)	(-5.77)	(-0.94)

Table XII
Test of Discontinuity in Expected Returns

In each year, we first sort stocks into quintiles based on one of the five firm characteristics: SIZE, BM, MOM, NS, and ILLIQ, and then compute changes in total return (ΔTR) and changes in continuous returns (ΔCR) for each quintile. Specifically, ΔTR is the change of total stock return from a year before jump (July of t-1 to June of t) to a year after jump (July of t+1 to June of t+2). ΔCR is the change of the continuous return component from a year before jump (July of t-1 to June of t) to a year after jump (July of t+1 to June of t+2). This table reports the time series averages of return changes for each quintile and their time series t-statistics, for the entire sample period (1927/07-2005/06) and two subperiods (1927/07-1962/06 and 1962/07-2005/06).

Quintile	SIZE		BM		MOM		NS		ILLIQ	
	ΔTR	ΔCR	ΔTR	ΔCR	ΔTR	ΔCR	ΔTR	ΔCR	ΔTR	ΔCR
Panel A: Holding period 1927/07-2005/06										
Q1	12.31	10.41	-12.69	-12.53	43.02	34.68	-1.93	-1.70	-5.46	-5.90
Q2	0.07	0.17	-3.45	-4.15	20.81	17.82	-3.25	-3.93	-4.85	-5.29
Q3	-3.93	-3.97	-0.01	-0.18	5.65	5.14	-1.33	-2.15	-2.56	-2.87
Q4	-8.39	-7.89	2.65	2.78	-14.06	-11.61	-5.04	-5.13	-0.61	-0.47
Q5	-7.25	-6.87	6.49	6.12	-64.00	-55.45	-5.73	-7.12	5.14	5.27
Q5-Q1	-19.56	-17.28	19.18	18.65	-107.02	-90.13	-3.80	-5.43	10.60	11.17
t-Stat	(-6.33)	(-6.07)	(3.88)	(3.95)	(-16.90)	(-15.76)	(-0.97)	(-1.40)	(3.25)	(3.56)
Panel B: Holding period 1927/07-1962/06										
Q1	13.09	11.56	-7.60	-7.38	40.95	35.50	-1.89	-1.63	-4.60	-4.31
Q2	0.43	0.81	-0.24	-1.42	20.90	18.55	-6.37	-7.71	-3.93	-4.39
Q3	-0.89	-1.09	-0.39	-0.56	6.04	5.11	-1.08	-3.08	-1.27	-1.72
Q4	-5.83	-5.71	2.31	2.57	-13.76	-11.76	-6.21	-5.65	0.78	0.15
Q5	-5.50	-5.21	6.44	6.48	-54.01	-48.17	-4.73	-6.50	7.52	7.54
Q5-Q1	-18.59	-16.77	14.05	13.86	-94.97	-83.67	-2.84	-4.87	12.12	11.86
t-Stat	(-3.77)	(-3.36)	(1.61)	(1.62)	(-8.87)	(-8.31)	(-0.37)	(-0.62)	(2.27)	(2.10)
Panel C: Holding period 1962/07-2005/06										
Q1	11.67	9.47	-16.83	-16.73	44.70	34.01	-1.97	-1.75	-6.16	-7.18
Q2	-0.22	-0.35	-6.06	-6.37	20.74	17.23	-0.71	-0.85	-5.61	-6.02
Q3	-6.41	-6.32	0.30	0.13	5.34	5.16	-1.54	-1.40	-3.62	-3.82
Q4	-10.47	-9.67	2.92	2.95	-14.31	-11.49	-4.09	-4.71	-1.75	-0.98
Q5	-8.67	-8.21	6.53	5.83	-72.13	-61.37	-6.55	-7.63	3.21	3.42
Q5-Q1	-20.34	-17.69	23.35	22.56	-116.83	-95.38	-4.58	-5.88	9.37	10.61
t-Stat	(-5.15)	(-5.46)	(4.24)	(4.51)	(-16.09)	(-14.99)	(-1.34)	(-1.95)	(2.31)	(3.08)