Investor Response to Jumps in Mutual Fund Returns

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ABSTRACT

While a considerable amount of research examines how investors allocate capital across mutual funds in response to fund performance, relatively little attention has been paid to investor response to fund risk. We posit that when faced with a discontinuity in returns (a stochastic jump) investors receive a clear signal about the riskiness of the fund and respond accordingly. We find that jumps occur regularly in fund returns (approximately 8 percent of funds monthly) and result in economically significant cash outflows the following month (as much as 60 basis points). Funds face outflows when other funds either inside or outside their investment objective experience jumps, even if they themselves did not jump. This suggests investors interpret jumps primarily as a signal of systematic risk. Controlling for systematic jumps, funds with positive non-systematic jumps see cash inflows, suggesting investors interpret non-systematic jumps as a proxy of manager ability and not risk.

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Why studying jumps in mutual fund returns? The mutual fund literature has spent decades questioning the rationality of fund investors. Not only does research strongly suggest active funds underperform[1], but investors continue to supply capital to these funds in spite of their underperformance (see e.g., Gruber (1996)). While Berk and Green (2004) suggest such performance may be the expected equilibrium given a competitive market for capital among funds, it is not empirically clear investors rationally allocate assets among active funds. Cash flows appear unresponsive to poor performance (see e.g., Sirri and Tufano (1998)), weakly responsive to moderate performance (see e.g. Chevalier and Ellison (1997)), and excessively responsive to high performance[2] and fund characteristics not related to performance.[3]

Additionally, Avramov and Wermers (2006) contend investors should consider fund exposure to risk in addition to performance when allocating capital across multiple funds. Whether investors do so remains an empirically open question.[4] The motivation for the consideration of risk stems from modern portfolio theory, which suggests all systematic risks should be factored into asset allocation. While many investors generally interpret this to imply asset covariances, risk is actually agnostic to the source of risk as long as it is systematic. A stochastic jump, a break in an otherwise smooth Gaussian

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[1] While some research has found stock picking ability through the examination of holdings (see e.g., Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000), and Frank, Poterba, Shackelford, and Shoven (2004)) or some subset of firms which appear to outperform (see e.g., Chen, Huang, Hong, and Kubic (2004), Kacperzcyk, Sialm, and Zheng (2005), Cremers and Petajisto (2009)), the general consensus is that, adjusted for risk, funds underperform (see e.g., Jensen (1968), Elton, Gruber, Das, and Hlavka (1993), Malkiel (1995), Carhart (1997), Carhart, Carpenter, Lynch, and Musto (2002), French (2008), and Fama and French (2010)).

[2] Considerable research documents investors chasing fund returns. See e.g., Ippolito (1992), Sirri and Tufano (1998), Patel, Hendricks and Zeckhauser (1990), Kane, Santini, and Aber (1991), Gruber (1996), Zheng (1999), Goetzman and Peles (1997), Bollen (2007), and Bailey, Kumar, and Ng (2011). This appears to be at the detriment of sensitivity to poor performance, as several papers have found the relation between flows and performance to be non-linear and concentrated on high performance (see e.g. Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Gruber (1996), Goetzmann and Peles (1997) Nanda, Wang, and Zheng (2004)).

[3] Investors appear to respond to advertising (Jain and Wu (2000)), 5-star Morningstar ratings (Del Guercio and Tkac (2008)), and name changes (Cooper, Gulen, and Rau (2005)).

[4] Cederburg (2008) finds evidence that investors respond to risk factor loadings when allocating capital to funds, conditional on the state of the U.S. business cycle. Siri and Tufano (1998) find no relation between flows and fund return volatility while Barber, Odean, and Zheng (2005) find lower inflows for fun ds with higher volatility. Some implicitly test investor response to risk by examining flow response to risk-adjusted returns (see e.g. Del Geurcio and Tkac (2002)). However, such specifications are joint tests and do not disentangle return and risk.

process, reveals discontinuity in an asset's returns.[5] That discontinuity in mutual fund returns, if correlated across multiple funds, is risk borne by fund investors not measured by the fund's standard deviation, covariance, beta, or any factor loadings.[6] If investors alter their allocation to funds following jumps, it suggests they are responding to a signal that those funds are exposed to more risk than previously perceived and provides evidence they are, to some extent, rationally considering risk in their asset allocation.

In this paper we examine whether investors consider risk when allocating capital across active mutual funds by measuring the responsiveness of cash flows to stochastic jumps in daily fund returns. Utilizing a sample of 6,695 actively managed funds across a wide cross section of investment objectives and BNS, we find that investors respond to jumps in daily returns by removing money from those funds in the following month. This occurs regardless of whether the jump is positive (22 basis point outflow) or negative (31 basis point outflow). Controlling for the objective adjusted return of the fund, a jump can result in as much as a 60 basis point outflow. Given a positive objective adjusted return results in a 74 basis point inflow, the relative outflow following a jump is economically significant, wiping out a large portion of the inflows the fund would have gained from outperforming its peers.[7] This relation is robust to the inclusion of other proxies of fund risk such as return standard deviation, skewness, and kurtosis.

This negative response to jumps may be due to perceived total risk, systematic risk, or neither. Perhaps, for instance, investors perceive jumps as a negative signal of manager ability and respond accordingly. Or investors perceive jumps as non-systematic risk and rebalance their allocation to

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5 Hence a stream of portfolio choice literature models asset returns as following a Browning motion with stochastic jumps process considering either idiosyncratic (see e.g., Liu, Longstaff, and Pan (2003)) or systematic (Das and Uppal (2004)) jumps.

6 Huang and Tauchen (2005) show that jumps increase volatility. However, Das and Uppal (2004) demonstrate that volatility does not fully capture the risk created by discontinuous returns. While jumps are clearly correlated with kurtosis, they are a risk not measured by any higher moment of the return distribution.

7 This outflow is also large relative to the mean monthly fund cash inflow of 111 basis points during our sample.

diversify away that risk. To directly test if this effect is driven by systematic risk, we additionally examine fund cash flows following jumps, which occur in other fund's returns. When a large portion of funds either in the same objective or across all funds jumps (what we refer to as a systematic jump), funds without jumps experience outflows (as much as 57 basis points). For objective jumps, this occurs after both positive and negative systematic jumps, suggesting investors perceive such jumps as a signal of systematic risk in the underlying asset or trading strategy. Interestingly, once we control for systematic jumps, we find investors view jumps uncorrelated with systematic jumps (what we refer to as non-systematic jumps) differently. Negative non-systematic jumps result in outflows (as much as 48 basis points) while positive non-systematic jumps result in inflows (as much as 38 basis points).

Examining financial markets, the extant literature also shows stock returns exhibit jumps relative to the rather smooth variation typical of a Gaussian distribution. Jumps might arise for a number of different reasons including shocks to some important factor such as energy prices, sudden changes in the parameters of the conditional return distribution, and extreme events like political upheaval in a particular country. There could be too many small changes, inliers and/or too many large changes, outliers. In modern financial economics, modeling financial price changes that implies the price series is the realization of a continuous-time diffusive process plays an important role. The assumption of local continuous Gaussianity simplifies the hedging calculations that underlie derivatives pricing. Although the diffusive models are of great analytical convenience, such models are empirically inconsistent with the extreme violent movements. The recent financial crisis provides good evidence as it highlights the importance of systemic risk in the current environment of globally integrated financial markets and fast trading technology. Jump diffusions with discontinuous sample paths provide a more appropriate empirical model for financial price series (Huang and Tauchen, 2005; Eraker et al 2003).

Why are correlated jumps in returns important? Since at least the stock market crash in October 1987, investors, policy makers, and researchers have attempted to examine whether and how shocks to one financial market spread to other markets. A large literature on financial market linkages and financial contagion has emerged accompanying the Mexican, Asian, and LTCM crises in the 1990s. A growing body of theoretical research points at an important role of market liquidity. Both practitioners and media introduce the terms, "sudden liquidity dry-ups", "liquidity crashes" or "liquidity black holes". These liquidity shocks induce shocks to security prices and spillovers to other markets. Although the shocks in stock markets both domestically and internationally are investigated, the shocks in mutual funds, their propagation, and their impact to investment fund flows are not.

A large body of literature examines spillover effects from one market to another using a plethora of different methods. For instance, Bae, Karolyi and Stulz (2003) define coexceedance as the simultaneous incidence of extreme returns or those in top or bottom 5% of the return distribution by country over the whole sample period and explain the determinants of such coexceedances using multinomial logit models. Hartmann, Straetmans, and de Vries (2004) apply extreme value theory and document that the actual probability of a simultaneous crash on two markets is much higher than the expected probability under the assumption that extreme events are independent across markets. Chiang, Jeon, and Li (2007) and Pukthuanthong and Roll (2011) apply a dynamic conditional correlation (DCC) model whereas Rodriguez (2007) use a switching copula approach to examine spillover effects. In this study, we follow Pukthuanthong and Roll (2015) and apply a statistical jump measure to identify a shock. Of course, there are various jump measures including those non-parametric ones devised by BNS, Jiang and Oomen (2008), Lee and Mykland (2008), and Jacod and Todorov (2009). The parametric measures include maximum likelihood, GMM, and Bayesian. The advantage of our method is that it adheres closely to the intuitive view of a shock to financial markets as a discontinuous event in an otherwise continuous time-series. Moreover, it does not require arbitrary definitions of extreme events, it is easy to compute and does not need the estimation of a large number of parameters. Further, it can indicate the particular day when the shock(jump) occurs and detect both fund-specific jumps and jumps that are transmitted to other funds, without a need to make assumptions regarding the joint distribution of variables across multiple markets. Potential disadvantages are that on days with many observations in the tail of the full-sample distribution, it may not classify observations that could be regarded as extreme under different methods as jumps. It may not identify a series of changes in the variables of interest that may accumulate to a large change but do not constitute discontinuous jumps.

Stochastic return jumps provide a unique laboratory for examining investor response to changes in risk. It may be difficult for even sophisticated investors to identify structural shifts in a fund's total or systematic risk, as estimation error can make trends, temporary, or even permanent shifts impossible to confidently measure except over very long periods of time. However, discontinuities in returns are relatively easier to identify. If sufficiently large, one may even be able to identify a jump visually on a stock chart. Now, for any specific fund, we do not know whether a jump is an actual change in risk or merely a signal of the underlying risk which already exists in the fund. But regardless, that jump is a relatively unambiguous measure of the fund's risk we can measure precisely and therefore measure a precise response the following month.

This paper makes several contributions to both the mutual fund and stochastic jump literatures. To our knowledge, we are the first to document the existence of stochastic jumps in mutual fund returns. Given funds generally hold portfolios of over 100 securities, investors may assume funds are diversified with smooth returns. However, considering aggregate market returns jump (Pukthuanthong and Roll (2015)), it is reasonable to expect jumps in fund returns. We find that roughly 8 percent of mutual funds experience a return jump each month and investors respond to them by withdrawing cash. Additionally, we find investors respond to jumps that are correlated across an investment objective or across all funds, suggesting they view these jumps as systematic risk. Interestingly, we find investors reward positive non-systematic jumps, suggesting they view them as a signal of managerial ability. Although we are the first paper examining mutual fund returns, we are not the only work applying jumps in mutual fund area. In a concurrent paper, Jiang et al (2016) also utilize BNS to measure jumps in daily returns of stocks held by mutual funds. They term stocks that create a large surprise during corporate events as high information intensity stocks and document funds that hold stocks with jumps exhibit large performance dispersion.

This paper adds empirical application to the stochastic jump literature. Much of the literature is motivated by the need to better identify systematic risks for more accurately optimized portfolio allocation (see e.g., Bollerslev, Law, and Tauchen (2008)). In this paper, mutual funds act as a laboratory to demonstrate investors can not only identify jumps, but respond to systematic jumps by reallocating capital across funds. Also, given discontinuous returns impact the estimation of risk factor loadings (see e.g. Todorov and Bollerslev (2010)), identifying jumps in mutual funds motivates additional work in empirical measurement of systematic risk in managed portfolios.

Our paper sheds light on a number of important issues. In today of complex, dynamic, and interconnected global financial system, it is important for investors and regulators to understand whether and how shocks are propagated from one fund to another, how investors react to the occurrence and propagation of shocks to mutual fund returns, and how strong cross-fund linkages are within and across objective funds. Our results may help investors make better decisions regarding mutual fund investment, fund managers to develop better risk management policies, and regulators to develop better policies to reduce financial fragility in mutual funds.

I. Hypothesis Development

Mutual funds generally hold portfolios of 100 or more different securities, suggesting a level of diversification even for funds concentrated inside industries (Kacperczyk, Sialm, and Zheng (2005)), which may smooth returns sufficiently to eliminate discontinuities. However, diversification does not inherently eliminate jumps. Substantial evidence exists for discontinuous returns in even highly liquid equity portfolios (see e.g., Eraker, Johannes, and Polson (2003) and Huang and Tauchen (2005)) and across entire markets (Das and Uppal (2004), Asghartian and Bergtsson (2006), and Pukthuangthong and Roll (2015)). Additionally, active funds may hold fixed income (Cici and Gibson (2012)) or option (Cici and Palacios (2015)) which, due to their market characteristics, are highly likely to have discontinuous returns (see e.g., Eraker (2004), Duffie, Pan, and Singleton (2000)). A fund's investors may even cause discontinuous returns. In providing liquidity to investors, funds forfeit returns (Edelen (1999)). If the liquidation of assets to cover outflows is large enough, it could cause a jump in returns. This leads us to our first hypothesis:

Hypothesis 1: Mutual funds have discontinuous returns.

The existence of discontinuities in mutual fund returns does not, by itself, prove investors should or do react to them. The fact the jump literature has spent decades carefully developing more sophisticated jump detection techniques (see e.g., Jarro and Rosenfeld (1984), Lee and Mykland (2008)) may mean investors are unable to identify jumps when they occur (or can only identify extremely large jumps). And even if they can identify them, they may only be concerned with jumps to the extent they impact the distribution of their portfolio's returns (Pan (2002)). They could only alter their capital allocation when jumps are large enough to alter a fund's standard deviation or kurtosis. If that is the case then they aren't really responding to jumps, but to the overall risk of the fund.

However, a significant amount of research says investors should care about jumps. Todorov and Bollerslev (2010) and Bollerslev, Li, and Todorov (2016) show that jumps alter betas while

Bollerslev, Law, and Tauchen (2008) shows jumps represent systematic risk not captured in beta. If true, investors should factor jumps into their optimal portfolio allocation (Das and Uppal (2004), Ait-Sahalia, Chacho-Dias, and Hurd (2009)). Given discontinuous returns are definitionally riskier than continuous returns, investors should remove assets from funds, which experience jumps, even when jumps increase returns. This gives us Hypothesis 2:

Hypothesis 2: Investors remove capital from mutual funds which experience stochastic jumps.

Considering jumps as risk, the jump literature suggests investors should only respond to systematic jumps (see e.g., Das and Uppal (2004)). Beside the fact that we observe market-wide return jumps (Pukthuangthong and Roll (2015)), there are reasons to expect correlation in jumps across mutual funds. Mutual funds with similar investment objectives tend to have considerable overlap in holdings (Grinblatt, Titman, and Wermers (1995)). This is partially because of the limited number of securities available in certain classes, partially because of clustering around the same benchmark used to assess fund performance (Chan, Chen, and Lakonishok (2002)), and partially because of intentional mimicking of direct competitor trading strategies (Cohen, Coval, and Pastor (2005)). Additionally, many macroeconomic events (i.e. GDP growth, interest rate changes) may impact assets across multiple investment objectives. Regardless of the reason, investors should expect a market or asset class wide jump to impact multiple funds simultaneously. If investors are responding to systematic risk, we should expect assets to flow out of funds not just when the fund jumps, but when a large number of other funds jump. This gives us Hypothesis 3:

Hypothesis 3: Investors remove capital from mutual funds following systematic stochastic jumps.

As previously discussed, if the only reason investors update their asset allocation in response to jumps is risk, we might expect them to only do so when those jumps are systematic (see e.g., Bollerslev, Law, and Tauchen (2008)). However, as mutual funds are intermediaries and not assets themselves, there are two possible responses investors may have to non-systematic jumps. First, investors may update their allocation across funds inside an investment objective following jumps to better diversify away non-systematic risk. As an example, consider two small cap growth funds (Fund X and Fund Y) which have the same number of stocks in their portfolios, but X has a more concentrated portfolio than Y. X is inherently more susceptible to non-systematic jumps, and when one occurs investors allocated some capital from X to Y. This leads to Hypothesis 4A:

Hypothesis 4A: Investors remove capital from mutual fund which experience non-systematic stochastic jumps.

This is not, however, the only conclusion investors could reach concerning non-systematic jumps. Given the example above, suppose Fund X has a more concentrated portfolio because it believes a subset of the stocks it owns are mispriced (these are active funds, after all). A potential payoff of that strategy is a positive stochastic jump. Conversely, a potential negative consequence of that strategy is a negative stochastic jump if the fund misestimated the mispricing in its active portfolio. It is therefore possible that investors interpret non-systematic jumps as proxies of managerial ability and respond accordingly. This gives us Hypothesis 4B:

Hypothesis 4B: Investors remove capital from mutual funds which experience negative non-systematic stochastic jumps, but add capital to mutual funds which experience positive non-systematic stochastic jumps.

II. Data and methodology

Our sample includes all funds in the CRSP Open-Ended Mutual Fund Database with Lipper objective codes on a list of 14 equity and fixed income investment objectives (Growth, Growth and Income, Small Cap, Aggressive Growth, Equity, Investment Grade, Non-Investment Grade, Treasuries, Mortgage, General, Municipal, Balanced, International, Alternative Investments) and have daily returns reported between January 2001 and December 2012.[8] We utilize the BNS measure which uses daily returns to identify jumps over four-day windows with a 95% confidence level.

Many asset pricing models assume stock prices follow a continuous time Brownian motion (see e.g., Black and Scholes (1973)). While stock price movements are clearly discrete (bound to move no less than tick size and at the maximum speed allowed by an exchange's infrastructure), it is generally reasonable to fit a continuous time model to discrete stock returns given weak assumptions (see e.g. Kloeden and Platen (1992)). However, when doing so it is possible the discrete return is actually composed of two separate returns, one a continuous underlying Brownian motion and the other a series of discrete discontinuous movements independent of the Brownian motion (a jump process). Anecdotal identification of jumps in return series is possible through visual inspection if the jump process is large enough. However, identification of smaller jumps or jumps across a large cross section of assets necessitates a statistically reliable empirical approach.

While the details of the BNS jump detection calculation are provided in the Appendix, the intuition is as follows. Barndorff-Nielsen and Sheppard (2004) develop a measure of variation (quadratic variation) in returns called bi-power variation, which allows the variation in an asset's discrete returns to be decomposed into its continuous and non-continuous parts. BNS uses the ratio of bi-power variation to total variation as a proxy for a discontinuous return. The squared variation is obtained by summing up the squared daily observations during the time interval (one month or 22 working days in our case), while the bipower variation is based on the scaled summation of the products of the absolute values of the current and lagged daily observations. The bipower and squared variations on a particular day are similar in the absence of jumps, while the bipower variation is significantly smaller than the squared variation if the time-series has a jump on that day. Applied

[8] We rerun our analysis using just equity funds. While we find no reaction to non-systematic jumps we find a strong negative relation between systematic jumps and flows, suggesting our risk explanation (Hypothesis 3) holds in that subsample common to many mutual fund cash flow research.

empirically (as done in BNS, Lee and Mykland (2008), and others), this ratio is the mean realized volatility of returns over a four-day window to mean realized volatility of returns over the 22 days prior to that window. That ratio is then run through a function to turn it into a normally distributed variable whose significance can be ascertained through a one-sided t test. BNS is a method "by far the most developed and widely applied of the different methods" (Bollerslev, Law, and Tauchen, 2008, p. 239) and the best jump measure in the simulations of Pukthuanthong and Roll (2015). This approach is appealing in that it does not require a fully observed state variable as in Ait-Sahalia (2002). This is not the first study that apply high-frequency jump technology for detecting jumps in a less frequency basis. Jiang et al (2016) apply BNS to measure jumps of daily stock returns. Pukthuanthong and Roll (2015) apply jumps to international market indexes and conclude jump measures are reliable, possess satisfactory when jumps are frequent, relatively large compared to nonjump variation in returns, and commove often, which are what we find in this study (see Table 1). Further, many intra-day large jumps are caused by market microstructure noises and illiquidity and they tend to revert quickly over time (Christensen, Oomen and Podolskij, 2014). Our jump application on a daily return with significant economic magnitude of jumps during one-month interval mitigates this concern.

We therefore identify jumps using a rolling 26-day window (days t-3 through t as the window to test for a jump and days t-26 through t-4 for realized variation to calculate the test statistic). If a four-day period is significant for a jump at a 5 percent significance level, we identify that month as a jump month. We then categorize that jump as positive or negative based on the sign of the cumulative return over that four-day period. If a fund had multiple jumps in a given month (there are not many), we sign the jump as the sign of the largest absolute cumulative return.

Table 1 Panel A shows our total sample includes 6,695 funds and 427,298 fund months. During the entire time period, there are approximately 36,000 months with jumps, with 8.45% of funds experiencing a jump each month, on average. This implies a 65% unconditional chance of experiencing at least one jump in the entire year. Jump frequency varies across investment objectives. Municipal funds have the highest probability of a jump (at 33.72% each month), with the probability of at least one jump in the year is 99.28%. Small Cap funds have the lowest probability of a jump (at 1.90% each month), and the probability of at least one jump during a year is 20.56%. Our motivation for including both equity and fixed income funds stems from Panel A. Not only are fixed income funds are more likely to jump, they also show a greater cross-sectional variation in jump frequency across objectives. General fixed income and balanced funds have a fairly low frequency of jumps (~4 percent), investment grade and treasuries have a moderate frequency (~15 percent), and non-investment grade, mortgage, and municipal with high jump frequency (25+ percent).

Panel B reports time series summary statistics of the cross-sectional percentage of funds with a jump each month and the cumulative four-day return around the identified jump. The average return of four-day window around jumps is -0.06%, which appears small. However, this is due to positive and negative jumps canceling each other out, on average. We therefore include the summary statistics of the absolute value of returns, showing a mean (median) magnitude of 100 (70) basis points. As a point of reference, the median daily return for our sample is 3.85 basis points (or 15.39 basis points per four-day window). So the jumps we identify do appear to be economically large.

Overall, Table 1 provides substantial evidence in support of Hypothesis 1. Mutual funds experience return jumps. Jumps appear to be frequent and economically meaningful.

III. Empirical Results

As our remaining hypotheses pertain to how investors update their asset allocation given updated information on fund risk and return, we employ a specification similar to Sirri and Tufano (1998). We regress fund net cash flows on the prior period's fund characteristics (i.e. total net assets, return, jumps), controlling for net cash flows into the fund's investment objective. We define net cash flow as:

$$Flow_t = \frac{TNA_t - (1+r_t)TNA_{t-1}}{TNA_{t-1}} \quad (1)$$

where TNA_t is the total net assets of the fund in month t, TNA_{t-1} is the total net assets in month t-1, and r_t is the return in month t. If investors neither purchased nor redeemed shares in month t the fund's TNA_t would equal their TNA_{t-1} multiplied by 1 + r_t, and $Flow_t$ would be zero. $Flow_t$ therefore represents the capital either added to or removed from the fund scaled by the prior month's TNA.

While Sirri and Tufano (1998) examine annual flows and performance, the identification of jumps is very precise to the day. We have no reason to believe an investor who identifies a jump would wait until the following year to update their allocation. We therefore observe all data on a monthly level. All regressions are Pooled OLS on monthly data with standard errors clustered by time (month) and investment objective.

We begin our analysis of flows with a simple regression of flows regressed on our two jump indicator variables (positive jumps and negative jumps), controlling only for the two variables the literature has previously identified as having the largest impact on flows: the log of total net assets of the fund and the flows into all funds in the same investment objective. These results are reported as Model 1 in Table 2. We note that both jump coefficients (*PJump* and *NJump*) are negative and significant. As these are indicator variables, their interpretation is straightforward. Holding all else constant, a fund with a positive jump sees 22 basis points of its assets flow out the following month. The effect is economically larger for negative jumps, which results in a 31 basis point outflow. This is our first evidence in support of Hypothesis 2. Investors respond to jumps by removing cash from the fund.

Model 1's analysis is admittedly simple, so we include four additional specifications in Table 2 to refine our examination of jumps and control for additional fund characteristics. Model 2 introduces a control variable called High Ret, which is an indicator variable equal to 1 if the fund outperformed its investment objective's mean return and 0 otherwise.[9] That also allows us to condition the flow response to jumps on both whether the jump was positive or negative and whether returns were high or low. As expected, high returns result in inflows (78 basis points). Turning to jumps, we don't really have an expectation on variation across the four jump scenarios, other than we still believe they will all be viewed negatively by investors. And this is what we find for three out of four jump scenarios. For instance, a positive jump in the presence of high returns results in the largest relative outflows (47 basis points). Examining the partial derivative of the equation with respect to high returns, we see that outperformance with no jump results in inflows of 78 basis points while outperformance with a positive jump results in inflows of only 31 basis points.

Model 3 includes three variables to control for fund fees. Expense fee is defined as the fund's expense ratio minus 12b-1 fees (in essence a proxy for management fee). While all three fees (expense, advertising, and loads) have a negative relation with flows, the relation between jumps and flows remains unchanged.

As the thesis of this paper is predicated on jumps representing risk, Model 4 includes controls for the higher moments of the fund's return distribution. Standard deviation, skewness, and kurtosis are all measured from daily returns during month t-1. Our biggest concern here is perhaps kurtosis, as there is a mechanical relationship between the tails of the return distribution and the probability of jumps occurring. While we find investors do not like standard deviation (a 1 percentage point increase in daily standard deviation reduces flows by 14 basis points), the coefficient on kurtosis is not

[9] Sirri and Tufano (1998) utilize and oft-used piecewise function to model performance, the most commonly used in the literature being three continuous variables representing objective-adjusted returns in the 0-20th percentile, 20th-80th percentile, and 80th-100th percentile. The reason we do not utilize that specification is that the fineness of the investor cash flow response to performance weakens the shorter the observed period of time. Using annual returns on our sample, we find the well-established asymmetric flow-performance relation. If we use quarterly returns, the relation is only slightly asymmetric (and better modelled with two piece-wise variables). Using monthly returns, flows are really only responsive to over/under performance (and not the magnitude of the return).

significant and, more importantly, does not impact the relation between jumps and flows. One interesting finding is that the coefficient on skewness is positive and significant. This is consistent with a long line of work suggesting investors (both rationally and irrationally) have a preference for skewness (see e.g., Barberis and Huang (2008), Conrad, Dittmar, and Ghysels (2013), Amaya, Christoffersen, Jacobs, and Vasquez (2015))

Model 5 is identical to Model 4, but includes investment objective fixed effects. Our objective flows variable already control for a lot of investor preference concerning objectives, so the inclusion of fixed effects is technically overkill. However, we still find a significant negative relation between both positive and negative jumps, conditioned on the fund having high returns. Overall, Table 2 is consistent, strong evidence in favor of Hypothesis 2. Investors do not like jumps and remove statistically and economically significant amounts of cash from funds in the month following a jump.

Given the magnitude of the jump/flow relation appears to be conditional on objective adjusted performance, we want to determine if it is conditional on fund characteristics. Most notably characteristics are related to risk expectations. If a jump is a signal of riskiness in the fund, then investors should respond more strongly to that signal if they perceive the fund as low risk. In Table 3 we divide our sample monthly three ways: (1) high and low expenses, (2) high and low tracking error, or (3) high and low return standard deviation, where high is above median and low is below median in month t. Low expense funds tend to be less active than higher expense funds, while low tracking error and low return standard deviation funds definitionally have less risk than their higher counterparts.

We find the negative relation between jumps and flows exists almost exclusively in low risk funds. Low expense funds with high returns see outflows following jumps, low tracking error funds see outflows following negative jumps, independent of fund performance, and low standard deviation funds see outflows regardless of whether the jump is positive or negative and regardless of whether returns are high or low. Only one jump coefficient loads significant for any high risk funds: high expense funds with high returns and a negative jump see outflows. Otherwise they see no flow relation with jumps.

As discussed in developing Hypothesis 3, the fact that investors react negatively to jumps in fund returns does not inherently imply they are responding to increased risk (though the results just discussed in Table 3 are quite consistent with a risk-based explanation). However, if investors perceive jumps as a measure of systematic risk then we would expect them to respond to jumps which are correlated across multiple funds, even if the fund itself doesn't experience a jump. We measure systematic jumps in two ways: the percent of funds which jump in a fund's investment objective and the percent of all funds in our sample which jump.[10] To verify the effect across positive and negative systematic jumps, we construct both measures using just positive jumps (SPJump) or negative jumps (SNJump).

Table 4 reports regressions of fund flows on fund jumps, systematic jumps, the interaction of the two, as well as all controls from Table 2. To avoid the interpretation of triple interaction effect we do not condition jumps on high and low fund returns, through our results are robust to such a specification. Model 1 reports coefficients using objective jumps and gives three interesting findings. First, both positive and negative systematic jumps are negative and significant, suggesting investors remove cash from funds when funds in their objective jump independent of whether the fund itself experienced a jump. This is direct support for Hypothesis 3, suggesting investors see objective jumps as systematic risk.

[10] We have examined an alternative measure of objective jump which runs the BNS measure on aggregated objective returns and believe it doesn't work well given our data. We have a relatively short time series (2001-2012) which spans only one full business cycle. So we end up with a couple objectives which never statistically jump and several which only have jumps during the financial crisis.

Second, controlling for systematic jumps, we can turn to PJump and NJump and see how investors respond to non-systematic jumps. As discuss previously, there is a tension here. Investors might perceive non-systematic jumps as risk and still withdraw assets (Hypothesis 4A). Or, they might see non-systematic jumps as a proxy or consequence of manager ability and respond accordingly (Hypothesis 4B). In Model 1 we find the coefficient on NJump remains negative (33 basis point outflow) while the coefficient on PJump is now positive (23 basis point inflow). This supports Hypothesis 4B.

Finally, we can examine when funds jump at the same time as other funds in their objective by looking at the four interactions (i.e. SPJump*PJump, SPJump*NJump). We don't have a clear expectation for all four of these interactions, as it is really only the same direction interactions (i.e. SPJump*PJump) that suggest systematic risk.[11] However, only the same direction interactions are significant. Investors perceive positive jumps negatively in the presence of positive objective jumps. This is consistent with Hypothesis 3 (systematic risk). Oddly though, the coefficient on SNJump*NJump is positive and significant. We don't have a satisfactory explanation for this finding other than that it is inconsistent with a risk explanation of objective jumps.

A question remains as to whether objective jumps are in fact systematic. If the jumps are contained inside an objective, the investors may still be responding to non-systematic risk when they remove cash from funds. We therefore conduct two additional analyses. First, we examine the correlations between objective jumps to determine whether or not they are systematic. Turning to Table 5 we find strong correlations across objectives in the same broad asset class. The top right half of the correlation matrix is positive objective jumps, and we see the growth objective strongly correlated with growth and income (79 percent), aggressive growth (70 percent), non-diversified equity

[11] It is not clear how to interpret any potential risk associated with a fund jumping in the opposite direction as the rest of their objective (i.e. they have a positive jump while several funds in their objective have negative jumps).

(38 percent), and small cap (46 percent). Turning to fixed income objectives we find a 42 percent correlation in positive jumps between investment grade and non-investment grade objectives and a 38 percent correlation between treasury and non-investment grade objectives. There is even correlation across objectives that may not appear to have a clear connection. There is a 32 percent correlation between the international and growth and income objectives and a 57 percent correlation between growth and balanced objectives.

The correlation across objective jumps is substantially stronger for negative objective jumps. International negative objective jumps are strongly correlated with growth and income (93 percent), growth (91 percent) and even aggressive growth (90 percent). Balanced objective jumps are highly correlated with small cap (71 percent) and growth and income (96 percent) jumps. Taken as a whole this correlation in jumps across investment objectives suggests some type of systematic effect (i.e. business cycle, interest rates).

Second, we return to Table 4 and more directly measure systematic jumps as the percent of all funds with a positive or negative jump in Model 2. Absent one coefficient, we find qualitatively similar results. Investors respond to negative systematic jumps by withdrawing cash and respond to non-systematic jumps with outflows when they are negative and inflows when they are positive. The only difference is there is no significant relation between positive systematic jumps and flows. Interestingly, we still find a positive coefficient on the interaction between negative systematic jumps and negative non-systematic jumps.

In an attempt to understand that positive coefficient of $SNJump_{t-1}*NJump_{t-1,}$ we need more information to accurately interpret the interaction, as NJump is an indicator while SNJump is continuous. Panel A of Table 6 reports summary statistics for SPJump and SNJump both for objective jumps and aggregate jumps. Considering objective jumps we see that the 90^{th} percentile values of SPJump and SNJump are 20.46 and 9.97 percent respectively. However, the coefficients reported on

SPJump and SNJump in Table 4, as well as their interactions, assume a change of 100 percent (an increase from 0 to 100 percent). For instance, the coefficient on SNJump is -0.0118, implying that if 100 percent of funds in the objective had a negative jump the fund would see a 118 basis point outflow. The problem with this interpretation is that we have no objectives with 100 percent negative jumps (the 90th percentile is 9.97 percent). So at the 90th percentile of SNJump a fund would see an 11.76 basis point outflow.

To fully understand the systematic and fund jump interactions we need to condition them on the magnitude of the systematic jump variable. Panel B of Table 6 reports the net marginal effect of a positive or negative jump conditioned on the value of SPJump and SNJump. Though the coefficient on SNJump*NJump is a positive 0.0136, the net marginal effect of a negative jump at the 90th percentile value of SNJump is still a 19 basis point outflow. Across all four interactions at any realistic values of SPJump and SNJump we find that positive non-systematic jumps result in inflows and negative non-systematic jumps result in outflows. Fully accounting for both the level effect and the interaction, these results again support Hypothesis 4B. Investors view non-systematic jumps as proxies of manager ability, responding positively to positive jumps and negatively to negative jumps. Turning to systematic jumps measures across our entire sample we find similar results. Though the 90th percentile of systematic jumps is lower (10.42 and 7.51 percent for positive and negative systematic jumps respectively) we again find in Panel C that the net marginal effect of a positive non-systematic jump is inflows and the net effect for negative non-systematic jumps is outflows.

IV. Conclusion

In this paper we examine whether mutual fund investors adjust their asset allocation to discontinuities in returns (stochastic jumps). We find that mutual funds experience jumps in returns. On average, 8.45 percent of funds experience a jump monthly and these jumps are economically large (several times larger in absolute terms than median daily returns). Investors do not like jumps, removing cash from funds following either positive or negative jumps. This effect is economically large, and can wipe out nearly all expected inflows when a fund outperforms its investment objective.

We attribute this response to investors perceiving systematic risk in jumps. Funds see cash outflows in the month following jumps in other funds in their investment objective or across our entire sample, even if they don't themselves jump. This effect holds across all low and high risk fund subsamples (subdivided by expenses, tracking error, and return standard deviation). Controlling for these objective-level systematic jumps we find investors respond differently to non-systematic jumps depending on the direction. Negative non-systematic jumps are followed by outflows while positive jumps are followed by inflows. We interpret these findings to suggest investors perceive non-systematic jumps as a proxy of manager ability (and not skill) and respond accordingly.

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Table 1: Jump Frequency

Our sample includes all funds in the CRSP Open-Ended Mutual Fund Database with Lipper objective codes which fall into the below 14 investment objectives and have daily returns reported between January 2001 and December 2012. Our total sample includes 6,695 funds and 427,298 fund months. Panel A reports the number of funds in each investment objective. % w/ Jumps is the percentage of funds in that investment objective which had at least one jump during our sample. Mean Jumps per Month is the time-series mean of the monthly fraction of funds with jumps in each objective. Panel B reports time-series summary statistics of the cross sectional percentage of funds with a jump each month and the cumulative four-day return around the identified jump. The percentile is based on jump returns.

Panel A: Investment Objective		Funds	% w/ Jumps	Mean Jumps per Month
Growth (GR, Equity)		1,533	77.43%	3.46%
Growth and Income (GI, Equity)		855	82.81%	4.18%
Small Cap (SC, Equity)		948	66.56%	1.90%
Aggressive Growth (AG, Equity)		219	73.52%	3.74%
Equity, non-diversified (EQ, Equity)		665	65.71%	2.57%
Investment Grade (INV, Fixed Income)		436	87.39%	15.07%
Non-Investment Grade (JUN, Fixed Income)		143	86.01%	25.97%
Treasuries (GOV, Fixed Income)		154	86.36%	14.89%
Mortgage (MOR, Fixed Income)		17	94.12%	23.48%
General (GEN, Fixed Income)		105	54.29%	4.02%
Municipal (MUN, Fixed Income)		561	93.76%	33.72%
Balanced (BAL, Equity and Fixed Income)		587	81.60%	4.46%
International (INT, Equity and/or Fixed Income)		459	74.95%	4.71%
Alternative Investments (ALT)		13	46.15%	2.43%
	Total	6,695	77.51%	8.45%

Panel B: Time Series	% of Funds with Jumps	Jump Return	Abs(Jump Return)
Mean	8.45%	-0.06%	1.00%
10^{th}	2.74%	-1.13%	0.13%
25^{th}	4.09%	-0.58%	0.34%
50^{th}	6.77%	-0.09%	0.70%
75^{th}	10.82%	0.41%	1.18%
90^{th}	13.17%	0.90%	1.94%
Stdev	7.21%	1.70%	1.52%
N (Per Month)	271	271	271

Table 2: Cash Flow Sensitivity to Jumps

Coefficients from pooled OLS of monthly net asset flow (in time t+1) on fund performance characteristics. The sample period is 2001 through 2012. Log(TNA) is the log of the fund's total net assets in time t. Obj Flow is the dollar holdings value weighted net asset flow into the fund's investment objective in time t+1. Jumps are divided into positive (PJump) and negative (NJump). High Ret (Low Ret) is high (low) return defined as an indicator variable equal to 1 if the fund outperformed (underperform) its investment objective's mean return and 0 otherwise. Jumps are identified using BNS jump measure. See the Appendix for detailed calculation. Expense fee is measured in excess of the 12b-1 fee. Stdev, Skew, and Kurt are the moments of daily fund returns during the month. t-statistics are estimated using standard errors clustered by time (months) and investment objective.

	(1)		(2)		(3)		(4)		(5)	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Intercept	0.0256	*22.56*	0.0214	*18.96*	00171	*13.71*	0.0195	*14.64*		
Log(TNA_{t-1})	-0.0030	*-22.54*	-0.0030	*-22.42*	-0.0016	*-14.04*	-0.0017	*-14.39*	-0.0019	*-16.42*
Obj $Flow_t$	0.2564	*2.03*	0.2573	*2.03*	0.2058	*1.94*	0.2026	*1.95*	0.1902	*1.96*
$PJump_t$	-0.0022	*-2.80*								
$NJump_t$	-0.0031	*-3.00*								
High Ret_{t-1}			0.0078	*19.58*	0.0075	*21.89*	0.0074	*21.87*	0.0074	*21.87*
$PJump_{t-1}$*High Ret_{t-1}			-0.0047	*-5.23*	-0.0046	*-5.84*	-0.0060	*-7.95*	-0.0025	*-3.53*
$NJump_{t-1}$*High Ret_{t-1}			-0.0037	*-2.64*	-0.0053	*-4.16*	-0.0053	*-4.15*	-0.0034	*-2.96*
$PJump_{t-1}$*Low Ret_{t-1}			0.0002	*0.17*	-0.0006	*-0.74*	-0.0021	*-2.53*	0.0012	*1.50*
$NJump_{t-1}$*Low Ret_{t-1}			-0.0024	*-2.17*	-0.0037	*-3.95*	-0.0035	*-3.77*	-0.0012	*-1.47*
Expense Fee_{t-1}					-0.3486	*-7.88*	-0.4095	*-8.93*	-0.6109	*-12.51*
12b-1 Fee_{t-1}					-0.3513	*-4.57*	-0.4034	*-5.24*	-0.5180	*-6.80*
Max $Load_{t-1}$					-0.0979	*-11.44*	-0.0943	*-11.00*	-0.0801	*-9.48*
Stdev(Ret_{t-1})							-0.1412	*-4.10*	-0.2969	*-7.93*
Skew(Ret_{t-1})							0.0006	*1.76*	0.0012	*4.11*
Kurt(Ret_{t-1})							-0.0001	*-0.75*	0.0000	*0.38*
Objectives Fixed Effects	No		No		No		No		Yes	
N	427,181		426,819		384,819		384,538		384,538	
Adj. R^2	0.0095		0.0122		0.0119		0.0125		0.0246	

Table 3: Cash Flow Sensitivity Subsamples

Coefficients from pooled OLS of monthly net asset flow (in time t+1) on fund performance characteristics. The sample period is 2001 through 2011. Log(TNA) is the log of the fund's total net assets in time t. Obj Flow is the dollar holdings value weighted net asset flow into the fund's investment objective in time t+1. Jumps are divided into positive (PJump) and negative (NJump) as described in Table 2. High Ret and Low Ret are high and low return as defined in Table 2. Jumps are identified using BNS jump measure. See the Appendix for detailed calculation. Expense fee is measured in excess of the 12b-1 fee. Stdev, Skew, and Kurt are the moments of daily fund returns during the month. Funds are classified into low/high expense, tracking error, and return standard deviation monthly by median value across all funds. t-statistics are estimated using standard errors clustered by time (months) and investment objective.

	(1)				(2)				(3)			
	Low Exp		High Exp		Low TE		High TE		Low Stdev		High Stdev	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
$Log(TNA_{t-1})$	-0.0024	*-15.97*	-0.0009	*-6.05*	-0.0015	*-10.1*	-0.0015	*-9.08*	-0.0017	*-11*	-0.0021	*-13.55*
$Obj\ Flow_t$	0.2459	*2.25*	0.1447	*1.73*	0.1902	*2.08*	0.1762	*1.86*	0.2636	*2.44*	0.1332	*1.66*
$High\ Ret_{t-1}$	0.0061	*12.77*	0.0084	*21.84*	0.0024	*6.60*	0.0114	*24.02*	0.0045	*10.65*	0.0101	*22.09*
$PJump_{t-1}$*$High\ Ret_{t-1}$	-0.0031	*-3.94*	0.0006	*0.39*	-0.0009	*-1.24*	-0.0015	*-0.65*	-0.0018	*-2.42*	-0.0008	*-0.28*
$NJump_{t-1}$*$High\ Ret_{t-1}$	-0.0030	*-1.89*	-0.0036	*-2.49*	-0.0035	*-2.51*	-0.0008	*-0.40*	-0.0037	*-2.56*	-0.0003	*-0.14*
$PJump_{t-1}$*$Low\ Ret_{t-1}$	0.0009	*1.04*	0.001	*0.71*	-0.0004	*-0.48*	-0.0027	*-1.12*	-0.0003	*-0.36*	-0.0050	*-1.40*
$NJump_{t-1}$*$Low\ Ret_{t-1}$	-0.0012	*-1.08*	-0.0014	*-1.25*	-0.0022	*-2.46*	-0.0023	*-1.49*	-0.0020	*-2.09*	-0.0011	*-0.67*
$Expense\ Fee_{t-1}$	-1.6149	*-19.99*	0.1915	*3.11*	-0.9672	*-18.06*	-0.4973	*-7.32*	-0.5944	*-10.69*	-0.6083	*-8.93*
$12b\text{-}1\ Fee_{t-1}$	-1.6077	*-14.05*	0.1085	*1.02*	-0.5699	*-6.67*	-0.5631	*-4.36*	-0.2938	*-2.90*	-0.7200	*-6.91*
$Max\ Load_{t-1}$	-0.0014	*-0.13*	-0.1094	*-10.03*	-0.0665	*-6.75*	-0.0849	*-6.61*	-0.0864	*-7.56*	-0.0716	*-6.50*
$Stdev(Ret_{t-1})$	-0.1239	*-2.09*	-0.4066	*-11.33*	-0.1450	*-2.69*	-0.3293	*-6.64*	-0.5361	*-8.08*	-0.2039	*-5.05*
$Skew(Ret_{t-1})$	0.0016	*4.23*	0.0008	*2.25*	0.0014	*3.81*	0.0012	*2.57*	0.0016	*4.42*	0.0004	*0.86*
$Kurt(Ret_{t-1})$	-0.0002	*-1.38*	0.0002	*1.57*	0.0001	*0.82*	-0.0001	*-0.57*	0.0000	*-0.37*	-0.0001	*-0.42*
Objectives Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	192,412		192,126		179,983		181,972		190,137		194,401	
Adj. R^2	0.0367		0.0184		0.0234		0.0259		0.0321		0.0218	

Table 4: Cash Flow Sensitivity to Fund and Objective Jumps

Coefficients from pooled OLS of monthly net asset flow (in time t+1) on fund performance characteristics. The sample period is 2001 through 2012. Due to the small number of funds in the Mortgage, General Fixed Income, and Alternative investment objectives they are omitted for this analysis. Log(TNA) is the log of the fund's total net assets in time t. Obj Flow is the dollar holdings value weighted net asset flow into the fund's investment objective in time t+1. Jumps are divided into positive (PJump) and negative (NJump) as described in Table 2. Objective Jumps are the percentage of funds with the same investment objective with jumps that month, with SPJump being positive jumps and SNJump being negative jumps. Aggregate jumps are the percentage of funds across our entire sample with jumps that month, with SPJump being positive jumps and SNJump being negative jumps. Jumps are identified using BNS jump measure. See the Appendix for detailed calculation. Expense fee is measured in excess of the 12b-1 fee. Stdev, Skew, and Kurt are the moments of daily fund returns during the month. t-statistics are estimated using standard errors clustered by time (months) and investment objective.

	(1) Objective Jumps		(2) Aggregate Jumps	
	Coef	t-stat	Coef	t-stat
$Log(TNA_{t-1})$	-0.0020	*-16.50*	-0.0020	*-16.79*
Obj $Flow_t$	0.1690	*1.76*	0.1851	*1.84*
High Ret_{t-1}	0.0072	*22.13*	0.0072	*22.13*
$PJump_{t-1}$	0.0023	*2.08*	0.0058	*4.27*
$NJump_{t-1}$	-0.0033	*-2.41*	-0.0044	*-2.83*
$SPJump_{t-1}$	-0.0054	*-1.90*	0.0044	*0.53*
$SNJump_{t-1}$	-0.0118	*-3.17*	-0.0095	*-2.24*
$SPJump_{t-1}*PJump_{t-1}$	-0.0072	*-2.38*	-0.0952	*-5.32*
$SPJump_{t-1}*NJump_{t-1}$	-0.0021	*-0.57*	0.0183	*0.82*
$SNJump_{t-1}*PJump_{t-1}$	-0.0036	*-0.66*	-0.0025	*-0.33*
$SNJump_{t-1}*NJump_{t-1}$	0.0136	*3.09*	0.0152	*2.75*
Expense Fee_{t-1}	-0.6533	*-13.13*	-0.6404	*-13.03*
12b-1 Fee_{t-1}	-0.5165	*-6.75*	-0.5113	*-6.69*
Max $Load_{t-1}$	-0.0750	*-8.77*	-0.0778	*-9.08*
$Stdev(Ret_{t-1})$	-0.3021	*-7.87*	-0.2891	*-7.03*
$Skew(Ret_{t-1})$	0.0011	*3.55*	0.0012	*3.96*
$Kurt(Ret_{t-1})$	0.0002	*1.56*	0.0001	*0.98*
Fixed Effects	Yes		Yes	
N	368,025		368,025	
Adj. R^2	0.0243		0.0249	

Table 5: Objective Jump Correlations

Time series Pearson correlations between the objective jump measures (percent of funds in objective with a jump). The top right half of the matrix is the correlations between positive objective jumps and the bottom left half is the correlations between negative objective jumps. For ease of identification all correlations greater than 30 percent are in bold. The objectives are defined in Table 1.

	AG	ALT	BAL	EQ	GEN	GI	GOV	GR	INT	INV	JUN	MOR	MUN	SC
AG	1	0.05	**0.38**	**0.54**	0.21	**0.60**	-0.16	**0.70**	0.04	-0.11	-0.06	-0.06	-0.03	0.29
ALT	0.08	1	0.04	0.00	0.02	0.04	0.17	-0.01	0.23	0.14	0.13	0.17	0.16	0.07
BAL	**0.95**	0.06	1	0.3	0.28	**0.76**	-0.10	**0.57**	**0.38**	-0.02	0.04	0.06	-0.06	**0.40**
EQ	**0.94**	0.07	**0.86**	1	0.07	**0.33**	-0.03	**0.38**	0.24	0.01	-0.02	0.10	-0.05	0.25
GEN	0.30	-0.04	**0.36**	0.26	1	**0.33**	0.10	**0.31**	0.09	0.20	0.03	0.02	0.08	0.25
GI	**0.97**	0.05	**0.96**	**0.95**	0.28	1	-0.08	**0.79**	**0.32**	0.01	0.02	0.04	-0.02	**0.47**
GOV	0.04	-0.06	0.10	-0.03	0.13	0.05	1	-0.06	0.17	**0.87**	**0.38**	**0.60**	**0.54**	-0.09
GR	**0.97**	0.06	**0.92**	**0.96**	0.22	**0.98**	0.04	1	0.17	-0.02	-0.06	0.02	-0.08	**0.46**
INT	**0.90**	0.02	**0.89**	**0.93**	**0.31**	**0.93**	0.17	**0.91**	1	0.18	0.00	0.25	0.24	0.08
INV	0.14	-0.02	0.18	0.10	0.23	0.15	**0.87**	0.13	0.15	1	**0.42**	**0.59**	**0.45**	-0.08
JUN	0.16	0.00	0.14	0.13	**0.45**	0.11	**0.38**	0.07	0.17	**0.34**	1	0.17	**0.46**	0.08
MOR	0.03	-0.12	0.02	0.07	-0.04	0.06	**0.60**	0.08	0.05	**0.45**	0.21	1	**0.35**	-0.04
MUN	-0.08	-0.04	-0.08	-0.07	0.01	-0.08	**0.54**	-0.08	-0.06	**0.55**	0.23	**0.33**	1	-0.08
SC	**0.80**	0.03	**0.71**	**0.85**	0.17	**0.79**	-0.09	**0.78**	**0.76**	0.05	0.14	0.02	-0.04	1

Table 6: Net Marginal Jump Effect

Panel A reports the time series means of cross sectional summary statistics of the percent of funds which have a jump each month in each objective (there are 14 observations each month). Panel B reports the marginal impact of jumps on flow given Model (1) in Table 4 and various conditions: Positive or Negative Jump and the magnitude and direction of objective jumps. For instance, a fund with a positive jump when 5 percent of the funds in that objective jump have a positive jump will have the marginal jump effect of 0.0023 - 0.0072(0.05) = 0.0022. A fund with a positive jump when 25 percent of the funds in that objective have a positive jump will have a marginal jump effect of 0.0023 – 0.0072(0.25) = 0.0005.

	Panel A: % of fund in objectives with jumps			
Percentile	Positive Objective Jump	Negative Objective Jump	Positive Aggregate Jump	Negative Aggregate Jump
10th	0.09%	0.02%	1.62%	0.55%
25th	0.38%	0.36%	2.65%	0.95%
50th	1.45%	1.52%	4.90%	1.93%
75th	10.22%	5.11%	7.83%	3.99%
90th	20.46%	9.97%	10.42%	7.51%

	Panel B: Marginal Impact of Jumps on Flow			
% of funds in Objectives with Jumps	Positive Jump * Positive Objective Jump	Positive Jump * Negative Objective Jump	Negative Jump * Positive Objective Jump	Negative Jump * Negative Objective Jump
1%	0.0022	0.0023	-0.0033	-0.0032
5%	0.0019	0.0021	-0.0034	-0.0026
10%	0.0016	0.0019	-0.0035	-0.0019
15%	0.0012	0.0018	-0.0036	-0.0013
20%	0.0009	0.0016	-0.0037	-0.0006
25%	0.0005	0.0014	-0.0038	0.0001
30%	0.0001	0.0012	-0.0039	0.0008
35%	-0.0002	0.0010	-0.0040	0.0015

	Panel C: Marginal Impact of Jumps on Flow			
% of funds in Aggregate with Jumps	Positive Jump * Positive Aggregate Jump	Positive Jump * Negative Aggregate Jump	Negative Jump * Positive Aggregate Jump	Negative Jump * Negative Aggregate Jump
1%	0.0048	0.0058	-0.0042	-0.0042
5%	0.0010	0.0057	-0.0035	-0.0036
10%	-0.0037	0.0056	-0.0026	-0.0029
15%	-0.0085	0.0054	-0.0017	-0.0021
20%	-0.0132	0.0053	-0.0007	-0.0014
25%	-0.0180	0.0052	0.0002	-0.0006
30%	-0.0228	0.0051	0.0011	0.0002
35%	-0.0275	0.0049	0.0020	0.0009

Appendix: Jump Measure: Barndorff-Nielson and Shephard (2004), hereafter BNS

BNS develops a test statistics based on comparing bipower variation with squared variation. To understand their test, consider the following notion and equations:

t, subscript for day

T_k, the number of days in subperiod k

K, the total number of available subperiods

$R_{i,t,k}$, the return (log price relative including dividends, if any)

for asset i on day t in subperiod k

The BNS bipower and squared variations are defined as follows:

$B_{i,k}$, bipower variation,

$$B_{i,k} = \frac{1}{T_k-1}\sum_{t=2}^{T_k}|R_{i,t,k}||R_{i,t-1,k}|$$

$S_{i,k}$, squared variation

$$S_{i,k} = \frac{1}{T_k}\sum_{t=1}^{T_k}\left(R_{i,t,k}\right)^2.$$

BNS proposes two variants of the quadratic versus bipower variation measure, a difference and a ratio. If the non-jump part of the process has constant drift and volatility, they show that $(\pi/2)B_{i,k}$ is asymptotically equal to the non-jump squared variation. Consequently, a test for the null hypothesis of no jumps can be based on $(\pi/2)B_{i,k} - S_{i,k}$, or $(\pi/2)B_{i,k}/Si_{,k} -1$. Under the null hypothesis, the standard deviations of this difference and ratio depend on the "quarticity" of the process, which they show can be estimated by

$$Q_{i,k} = \frac{1}{T_k-3}\sum_{t=4}^{T_k}|R_{i,t,k}||R_{i,t-1,k}||R_{i,t-2,k}||R_{i,t-3,k}|.$$

Define the constant $\upsilon = (\pi^2/4) + \pi - 5$. Then the difference and ratio statistics,

$$G_{i,k} = \frac{(\pi/2)B_{i,k} - S_{i,k}}{\sqrt{\upsilon(\pi/2)^2 Q_{i,k}}}$$

$$H_{i,k} = \frac{\left(\frac{\pi}{2}\right)(B_{i,k}/S_{i,k}) - 1}{\sqrt{\upsilon Q_{i,k}/B_{i,k}^2}}$$

are both asymptotically unit normal.

These statistics have intuitive appeal because the squared variation ($S_{i,k}$) should be relatively small if there is smooth variation, as with the normal distribution. On the other hand, if the price jumps on some days, those jumps are magnified by squaring and the statistics above should be small. Small values of G and H relative to the unit normal reject the null hypothesis of no jumps.

From our perspective, these statistics also have the benefit that they can be computed sequentially over calendar periods of various lengths.[15] For example, beginning with daily observations, they can be computed monthly or semiannually for each asset. Subsequently, the resulting monthly or semiannual statistics can be correlated across assets to detect whether jumps are related. When the assets are broad country indexes, this provides the opportunity to test for internationally correlated jumps. For example, to check whether countries j and i exhibit correlated jumps, one can calculate the correlation over k = 1,…,K between $G_{i,k}$ and $G_{j,k}$.

In previous papers, Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007) adopt the BNS method and develop a Z statistic for jumps using tri-power quarticity. The latter paper also develops a "staggered" version of bi-power variation to tackle microstructure noise that induces autocorrelation in the high-frequency returns. Zhang, Zhou, and Zhu (2009) use the BNS method to identify jump risk of individual firms from high-frequency equity prices in order to explain credit default swap premiums. Pukthuanthong and Roll (2015) apply the BNS method to the daily returns of international stock market indices.

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[15] There is a caveat to this claim. BNS assumes that the non-jump part of the process has constant mean and volatility, which rules out phenomena such as reductions in volatility with increasing prices, and vice versa. This should be only a minor annoyance, though, when the calendar period is fairly short.