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Aggregate Jump and Volatility Risk in the Cross-Section of Stock Returns

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ABSTRACT

We examine the pricing of both aggregate jump and volatility risk in the cross-section of stock returns by constructing investable option trading strategies that load on one factor but are orthogonal to the other. Both aggregate jump and volatility risk help explain variation in expected returns. Consistent with theory, stocks with high sensitivities to jump and volatility risk have low expected returns. Both can be measured separately and are important economically, with a two-standard-deviation increase in jump (volatility) factor loadings associated with a 3.5% to 5.1% (2.7% to 2.9%) drop in expected annual stock returns.

AGGREGATE STOCK MARKET volatility varies over time. This has important implications for asset prices in the cross-section and is the subject of much recent research (e.g., Ang et al. (2006)).[1] There is also evidence that aggregate jump risk is time-varying. For example, Bates (1991) shows that out-of-the-money puts became unusually expensive during the year preceding the crash of October 1987. His analysis reveals significant time variation in the conditional expectations of jumps in aggregate stock market returns. Santa-Clara and Yan (2010) use option prices to calibrate a model in which both the volatility of the diffusion shocks and the intensity of the jumps are allowed to change over time. They likewise find substantial time variation in the jump intensity process, with aggregate implied jump probabilities ranging from 0% to over 99%.

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[1] Considerable research examines the time-series relation between aggregate stock market volatility and expected market returns. See, for example, Bali (2008), Campbell and Hentschel (1992), and Glosten, Jagannathan, and Runkle (1993).

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While they examine the time-series relation between systematic jump risk and expected stock market returns, the question of how aggregate jump risk affects the cross-section of expected returns has received less attention.

The main objective of this paper is to provide a comprehensive empirical investigation of the pricing of time-varying jump and volatility risk in the cross-section of expected stock returns. In particular, we consider whether aggregate jump and volatility constitute separately priced risk factors. Several papers argue that aggregate volatility may be a priced factor in part because assets with high sensitivities to volatility risk hedge against the risk of significant market declines (e.g., Bakshi and Kapadia (2003), Ang et al. (2006)). This argument suggests that jump and volatility risk may be similar. In addition, as markets tend to be more volatile in times of extreme returns, separating jump and volatility risk is an empirical challenge. In this paper, we show that they are in fact different: they can be measured separately using option returns and they are both important economically. Economic theory provides several reasons why aggregate jump and volatility risk should constitute priced risk factors. The importance of these risks is now a fundamental premise of the option pricing literature (see, e.g., the reduced-form models in Bates (2000), Pan (2002), and Santa-Clara and Yan (2010)). General equilibrium models can be used to shed light on the economic mechanisms that drive jump and volatility risk premia. Naik and Lee (1990) introduce jumps into general equilibrium models, Pham and Touzi (1996) introduce stochastic volatility, and Branger, Schlag, and Schneider (2007) examine the equilibrium with both jumps and stochastic volatility.

While these models use standard preferences, Bates (2008) considers investors who are both risk and crash averse. Jump and diffusive risks are both priced even in the absence of crash aversion, but introducing crash aversion allows for greater divergence between the two risk premia. An important feature of the model in Bates (2008) is a representative investor who treats jump and diffusive risks differently, which formalizes the intuition that investors can treat extreme events differently than they treat more common and frequent ones.[2]

These models provide a rich framework in which both volatility and jump risk are separately priced. Investors seeking to hedge against changes in investment opportunities will find assets that covary positively with market volatility attractive, and thus require lower expected returns. Separately, investors who seek to insure themselves against tail events such as the recent financial crisis, that is, more extreme events that go beyond business cycle fluctuations in investment opportunities, will find stocks with a positive loading on jump risk attractive and thus require lower expected returns.

To examine the cross-sectional pricing of aggregate jump and volatility risk, we construct investable option trading strategies that load on one factor but

[2] Liu, Pan, and Wang (2005) examine the equilibrium when stock market jumps can occur and investors are both risk averse and averse to model uncertainty with respect to jumps; they obtain similar pricing implications for jump and diffusive risk.

are orthogonal to the other. Because traded S&P 500 futures options are highly liquid, their prices encode market participants' ex ante assessment of expected aggregate jump and volatility risk. These prices should therefore contain forward-looking information that we expect to be highly relevant for our analysis. The ex ante jump risk perceived by investors may be quite different from ex post realized jumps in prices because even high-probability jumps may fail to materialize in sample (Santa-Clara and Yan (2010)). Therefore, employing options alleviates the "Peso problem" in measuring jump risk from observed stock returns.

A straddle involves the simultaneous purchase of a call and a put option. Coval and Shumway (2001) motivate the use of delta-neutral straddles for studying the effect of stochastic volatility by their high sensitivity to volatility—they have large vegas—and their insensitivity to market returns. However, this only holds for small diffusive shocks. In a world with jumps, straddle returns are subject to hedging error due to the positive gamma of the options: if the underlying asset experiences a large move in any direction, the straddle will not remain delta neutral and will earn a positive return. This implies that straddle returns are affected by both volatility and jump risk. More importantly, this observation suggests alternative trading strategies that allow us to focus on each risk separately.

A strategy constructed to be market (i.e., delta) neutral and gamma neutral but vega positive is essentially insulated from jump risk and thus only subject to volatility risk. Similarly, a strategy that is market neutral and vega neutral but gamma positive is ideal to study the effects of jump risk. We show that both strategies can be constructed by setting up long/short strategies involving market-neutral straddles. Our resulting jump risk factor-mimicking portfolio (JUMP) is a market-neutral, vega-neutral, and gamma-positive strategy involving two at-the-money straddles with different maturities. Similarly, we construct the volatility risk factor-mimicking portfolio (VOL) by combining two at-the-money straddles with different maturities into a position that is market neutral, gamma neutral, and vega positive. The JUMP and VOL strategies are directly tradable strategies that are constructed to load on one factor while being orthogonal to the other. Empirically, we find that the returns on the two strategies are essentially uncorrelated.

Our approach to finding a premium for bearing volatility and jump risk closely follows Ang, Chen, and Xing (2006). Specifically, we estimate jump and volatility risk factor loadings at the individual stock level using daily returns, we sort stocks on the realized factor loadings estimated over a given time period, and we investigate whether stocks with higher volatility and jump betas have lower average returns contemporaneously (i.e., over the same period). This approach considers both requirements that must be met for any factor to be priced in the cross-section of stock returns. First, there must be a contemporaneous pattern between factor loadings and average returns. Therefore, our analysis focuses on uncovering contemporaneous relations between volatility and jump risk loadings and average stock returns. Second, the pattern should be robust to controls for various stock characteristics and other factors known to affect the cross-section of expected stock returns. Our focus is on uncovering contemporaneous effects because a contemporaneous relation between factor loadings and risk premiums is the foundation of a cross-sectional risk-return relation. In addition, we investigate whether future jump and volatility risk exposures can be predicted (and thus hedged), constructing investable stock portfolios ex ante that have ex post exposure to jump and volatility risk.

Our main result is that both aggregate jump and aggregate volatility are significantly priced risk factors in the cross-section of returns. Consistent with theory, we find that stocks with high sensitivities to volatility and jump risk have low expected returns, that is, volatility and jump risk both carry negative market prices of risk. Both factors are also important economically. Sorting stocks into quintile portfolios based on their contemporaneous jump betas, the long/short portfolio that buys stocks with high jump betas and sells stocks with low jump betas has an annual three-factor Fama–French (1993) alpha of −9.4% (t-statistic −4.44) for value-weighted portfolios. Similarly, using Fama–MacBeth (1973) regressions, we find that a two-standard-deviation increase across stocks in jump factor loadings is associated with a 3.5% drop in expected annual returns. Our results on the *cross-sectional* pricing implications of aggregate jump risk are thus entirely consistent with the results in the related time-series literature, which suggests that time-varying aggregate jump risk has a large effect on aggregate market returns. For example, Santa-Clara and Yan (2010, p. 435) summarize their empirical results by saying that "compensation for jump risk is on average more than half of the total equity premium."

We also find large compensation for bearing stock market volatility risk. When we sort stocks into quintiles based on their volatility betas, the long/short portfolio that buys stocks with high volatility betas and sells stocks with low-volatility betas has an annual value-weighted three-factor alpha of −2.7% (t-statistic −2.40). In Fama–MacBeth regressions that control for the Fama–French factors, a two-standard-deviation increase in jump factor loadings is associated with a 2.9% drop in expected annual returns. Importantly, jump risk does not subsume volatility risk and volatility risk does not subsume jump risk.

Our results are robust to using both a portfolio approach and Fama–MacBeth regressions, as well as to the inclusion of a battery of control variables (including controls for size, downside beta, conditional skewness and kurtosis, idiosyncratic volatility, and idiosyncratic skewness). After controlling for conditional skewness and downside beta (both of which are associated with the notion of jump risk), we observe a slight drop in the estimated market price of jump risk. Importantly, however, jump risk is different from conditional skewness and downside beta: across all specifications, the reward for bearing jump and volatility risk is always negative, stable, and both economically and statistically significant.

This paper is related to Ang et al. (2006, henceforth AHXZ). They find that stocks with high sensitivities to innovations in aggregate stock market volatility have low average returns, using the first difference in the CBOE VIX index as a proxy for innovations in volatility. They note that using other measures of aggregate volatility risk (such as sample volatility, extreme value volatility estimates, and realized volatility estimates constructed from high frequency data) produces little spread in the cross-section of average stock returns.

Because AHXZ do not investigate the pricing of jump risk in the cross-section of stock returns, their analysis does not separate jump risk from diffusion risk. Recent theoretical results in Du and Kapadia (2011) and Martin (2012), however, suggest that VIX is a biased measure of diffusion risk in the presence of jumps, with the degree of bias related to jump severity. Thus, the effects documented in AHXZ could be related to volatility risk, jump risk, or a combination of both. In contrast, we employ separate measures for jump and volatility risk to disentangle the corresponding asset pricing effects. Another advantage of our risk factors is that they are based upon a readily tradable option portfolio strategy.

While the pricing of jump risk has been documented extensively in the option pricing literature, the question of how aggregate jump risk affects the cross-section of expected returns has received less attention. Chang, Christoffersen, and Jacobs (2009) consider market skewness estimated from option data and find a negative market price of market skewness. If one views market skewness as a measure of jump risk, then this result seems inconsistent with economic intuition, as it implies a positive market price of jump risk. We differ from their study by constructing option-based measures that aim explicitly to proxy for jump risk. Our results are also different because we find evidence of a negative market price of jump risk, as suggested by economic theory.

Finally, our paper is related to the literature on tail risk and rare disasters. Starting with Rietz (1988), researchers have modeled the possibility of rare disasters, such as economic depressions or wars, to resolve the equity premium puzzle and related puzzles (e.g., Barro (2006) and Gabaix (2008, 2012)). Kelly (2012) uses firm-level stock price crashes every month to identify common fluctuations in tail risk across stocks and finds that past tail risk predicts future returns in the cross-section. The disasters in the rare disasters literature are similar to the jumps we are interested in, but there are some differences: disasters are extremely rare and they do not match well the short-dated options that we use in constructing the JUMP and VOL factors.

The rest of this article is organized as follows. Section I presents theoretical arguments that suggest aggregate jump and volatility risk should be priced in the cross-section. It also describes the construction of our tradable jump and volatility risk factors. Section II describes our data and the empirical design used to investigate whether jump and volatility risk are priced. Section III presents our main results on the pricing of jump and volatility risk in the cross-section of stock returns. Section IV examines the robustness of our results to the inclusion of a battery of control variables. It also examines whether our results on the pricing of aggregate jump and volatility risk are robust to the use of alternative nontradable jump and volatility proxies and investigates whether future jump and volatility risk betas can be predicted so as to construct investable portfolios with a spread in jump and volatility risk for hedging purposes. Section V concludes.

I. Aggregate Jump and Volatility Risk

This section presents theoretical motivation for the pricing of systematic volatility and jump risk in the cross-section of stock returns and describes the construction of our jump and volatility risk factor–mimicking portfolios.

A. Theoretical Background

Economic theory provides several reasons why aggregate jump and volatility risk should constitute priced risk factors. The existence of priced aggregate jump and volatility risk has been extensively documented in the option pricing literature. Briefly, Bates (2000) extends the Heston (1993) stochastic volatility model by incorporating jumps. The model features a square root process for the diffusive variance and a jump intensity that is proportional to the diffusive variance. In the model, aggregate market returns are affected by three factors: diffusive price shocks, diffusive volatility shocks, and price jumps. Using the Bates (2000) model, Pan (2002) shows that a substantial premium for time-varying jump risk is required to fit the joint time-series of stocks and options. In Pan (2002) it is somewhat difficult to disentangle the diffusion and jump risks because they are both driven by the same state variable, the diffusive volatility. Santa-Clara and Yan (2010) propose a quadratic model to better separate jump and volatility risk. They find large jump and volatility risk premia.

These papers use reduced-form models that assume a parametric pricing kernel that prices all three sources of risk, including the jump and volatility risk. The market prices of the risk factors determine how options are priced. While this approach is tailored to the objective of developing option pricing models, it does not illuminate the economic mechanism that may be at work. An alternative approach is to derive the pricing kernel from economic fundamentals in a general equilibrium framework. For example, in the Lucas (1978) pure exchange economy, consuming the aggregate dividend must be optimal for the representative agent, and thus the marginal rate of substitution process identifies the equilibrium pricing kernel. Naik and Lee (1990) introduce jumps into a continuous-time version of the Lucas (1978) model to price options on the aggregate market portfolio. Pham and Touzi (1996) introduce stochastic volatility into the model. Branger, Schlag, and Schneider (2007) examine the equilibrium with both jumps and stochastic volatility.

Bates (2008) points out that an implication of these models is that, with standard preferences, the relative sensitivities of the pricing kernel to diffusive and jump shocks are constrained, which also constrains the magnitude of the jump premium. Intuitively, this happens because the representative agent treats small and large moves similarly. Bates (2008) considers the equilibrium when agents are both risk and crash averse. In his model, crash aversion is roughly as important as risk aversion for the equity risk premium but significantly more important for the jump risk premium. Liu, Pan, and Wang (2005) obtain similar pricing implications for jump and diffusive risk when investors are both risk averse and averse to model uncertainty with respect to jumps. Large risk premia obtain in equilibrium when the representative investor treats jump and diffusive risks differently.

While these papers do not explicitly model the cross-section of stock returns, they feature stochastic discount factors that load on both jump and volatility risk, and thus stocks with different sensitivities to these factors earn different returns in equilibrium. For example, Yan (2011) considers a model in which stock returns and the stochastic discount factor follow correlated jump diffusion processes. He finds that stocks with systematic jumps that are more negatively correlated with jumps in the stochastic discount factor earn higher returns.

Regarding volatility risk, Campbell et al. (2012) and Chen (2002) extend the approximate closed-form ICAPM framework of Campbell (1993) to allow for stochastic volatility (but not jumps). They show that assets whose returns covary positively with a variable that forecasts future market volatility have low expected returns in equilibrium, provided that the representative investor is more risk averse than log utility. The underlying economic mechanism is that risk-averse investors reduce their current consumption in order to increase precautionary savings in the presence of increased uncertainty about market returns. Put differently, time-varying market volatility induces changes in the investment opportunity set by changing the expectation of future market returns, or by changing the risk-return trade-off (Campbell (1993, 1996)). Market volatility thus qualifies as a state variable in a traditional multifactor asset pricing model (see Merton (1973)): risk-averse agents demand stocks that hedge against the risk of deteriorating investment opportunities. This increases the prices of these assets, thereby lowering their expected return.

Concerning jump risk, starting with Rietz (1988) and Barro (2006), a growing body of research examines the aggregate effects of rare disaster risk, which is related to the jump risk that we consider. Gabaix (2012) extends this framework to accommodate disasters of time-varying severity. While he does not examine the cross-sectional implications of time-varying disaster risk, in his model assets that pay off more during times of high disaster risk command lower expected returns. These models provide useful intuition for our work, although there are significant differences between the rare disasters literature and our approach of constructing option trading strategies that load on jump risk. In particular, the jumps in the option pricing literature happen every few days or months and they affect consumption by relatively moderate amounts, whereas the jumps in the rare disasters literature happen much more rarely, but, when they do arise, they are devastating.[3] Also, rare disasters do not match well the short-dated options that we use in constructing our jump and volatility factors.

[3] For example, the rare disasters in Barro (2006) strike once every 50 years and are associated with a 37% drop in aggregate consumption.

B. Construction of Aggregate Jump and Volatility Risk Factors

B.1. Straddle Returns and Stochastic Volatility

Delta-neutral at-the-money straddles would appear to be a simple, readily tradable, and economically meaningful factor-mimicking portfolio for volatility risk. Coval and Shumway (2001) argue that, while delta-neutral straddle returns are not sensitive to market returns, they are sensitive to market volatility: when volatility increases straddles have positive returns and when volatility decreases straddles have negative returns. In other words, straddles have large sensitivities to volatility, that is, large positive vegas. That straddle returns are useful in investigating stochastic volatility can be seen through the lens of a simple stochastic volatility model. For example, in the Appendix, we show that, in the Heston (1993) stochastic volatility model, (excess) straddle returns are locally proportional to innovations in volatility, suggesting that straddle returns are a good proxy for volatility risk. While the result does not depend specifically on the Heston (1993) model and holds for generic stochastic volatility models, introducing jumps renders the link between straddle returns and volatility far more complicated. Intuitively, this is because straddle returns are subject to hedging error due to the gamma of the options: if the underlying asset experiences a large move, the straddle will not remain delta neutral and the straddle return will be positive because of the gamma effect. While this implies that straddle returns are affected by both volatility and jump risk, it also suggests alternative trading strategies that can be constructed to focus on each risk separately, as we now explain.

B.2. Jump and Volatility Risk–Mimicking Portfolios

Straddles have large sensitivities to volatility (large vegas), which makes them a natural proxy for volatility risk. However, straddles also have large gammas and are therefore also sensitive to jump risk. A strategy constructed to be market neutral and gamma neutral yet vega positive would be essentially insulated from jump risk and thus only subject to volatility risk. Similarly, a strategy that is market neutral and vega neutral but gamma positive would be ideal to study the effects of jump risk. Because the gamma of an option is decreasing in the time to maturity while the vega of an option is increasing in the time to maturity, both strategies can be constructed by setting up long/short portfolios involving market-neutral straddles with different maturities.

Each zero-beta straddle is constructed by solving the problem

$$r_{MN} = \theta r_c + (1-\theta) r_p, \tag{1}$$

$$\theta \beta_c + (1-\theta)\beta_p = 0, \tag{2}$$

where r_{MN} is the market-neutral straddle return, r_c is the return on the call, r_p is the return on the put, θ is the weight invested in the call, and β_c and β_p are the market betas of the call and the put options, respectively. To implement the strategy, we follow Coval and Shumway (2001) and use Black–Scholes option sensitivities.[4]

Our jump risk factor–mimicking portfolio (JUMP) is a market-neutral, vega-neutral, and gamma-positive strategy consisting of (i) a long position in one market-neutral at-the-money straddle with maturity T_1, and (ii) a short position in y market-neutral at-the-money straddles with maturity T_2, where $T_2 > T_1$ and y is chosen so as to make the overall portfolio vega neutral using Black–Scholes option sensitivities. The longer dated options have larger vegas, such that the number y of market-neutral straddles being sold is less than one. Similarly, the volatility risk factor–mimicking portfolio (VOL) that we propose is a market-neutral, gamma-neutral, and vega-positive strategy consisting of (i) a long position in one market-neutral at-the-money straddle with maturity T_2, and (ii) a short position in y market-neutral at-the-money straddles with maturity T_1, where $T_2 > T_1$ and y is chosen so as to make the gamma of the overall strategy zero using Black–Scholes option sensitivities. Again, because the shorter dated options have larger gammas, the number y of straddles sold is less than one, and the market-neutral straddles are constructed as above.

The JUMP and VOL strategies are directly tradable, and they are constructed to load on one factor while being orthogonal to the other. Empirically, we find that the returns on these two strategies are essentially uncorrelated, as we show in Section II.

II. Data and Empirical Methodology

This section describes our data and the empirical design we employ to investigate whether jump and volatility risk are priced in the cross-section of stock returns.

A. Empirical Methodology

Our research design follows Ang, Chen, and Xing (2006, henceforth ACX), who themselves follow a long tradition in asset pricing in considering the contemporaneous relation between realized factor loadings and realized stock returns (e.g., Fama and MacBeth (1973), Fama and French (1993), and Jagannathan and Wang (1996), among others). A contemporaneous relation between factor loadings and risk premiums is the foundation of a cross-sectional risk-return relation. Like Ang, Liu, and Schwarz (2010), we focus on individual

[4] Our empirical analysis employs American-style S&P 500 futures options. The implied volatilities are computed using a binomial tree and thus account for the early exercise feature in the options. Early exercise premia are especially small for futures options, as the underlying futures prices do not necessarily change at dividend dates. For example, Driessen and Maenhout (2012) find very small early exercise premia of around 0.2% of the option price for short-maturity futures options. Similarly, Coval and Shumway (2001) study European-style and American-style options and do not report significant effects of the early exercise feature on their results. If at all, the early exercise feature should add noise to our factor returns and thus should make it more difficult for us to find an effect.

stocks rather than portfolios as our base assets when testing the pricing of aggregate volatility and jump risk using cross-sectional data, as they show that creating portfolios ignores important information (specifically, stocks within particular portfolios having different betas) and leads to larger standard errors in cross-sectional risk premia estimates.

Our tests employ portfolio sorts in which, like ACX, we work at the individual stock level and sort stocks directly on their estimated factor loading estimated over a given time period, computing realized average returns over the same time period. To check the robustness of our findings, we also report the results of Fama–MacBeth firm-level second-stage regressions of returns on factor loadings that are estimated in first-stage regressions.

For each stock i we estimate factor loadings at the individual stock level using daily returns over rolling annual periods from the regression

$$R_t^i = \beta_0^i + \beta_{MKT_t}^i \cdot MKT_t + \beta_{MKT_{t-1}}^i \cdot MKT_{t-1} + \beta_{X_t}^i \cdot X_t + \beta_{X_{t-1}}^i \cdot X_{t-1} + \varepsilon_t^i, \quad (3)$$

where R_t^i is the excess return over the risk-free rate of stock i on day t, MKT_t is the excess return on the market portfolio (the CRSP value-weighted index) on day t, and X_t is the return on either the jump or the volatility risk factor–mimicking portfolio.

We control for potential issues associated with infrequent trading by including lagged risk factors (in the spirit of Dimson (1979)) and using the sum of the betas estimated for the contemporaneous and the one-period lagged risk factors. Of course, other factors play a role in the cross-section of returns, for example, the Fama–French factors; we do not model these effects in estimating the β_X^i loadings because doing so might add noise to the estimation and because we want to closely follow AHXZ. We do control for the three Fama–French factors when performing our cross-sectional asset pricing tests.

Like ACX, at the beginning of each year, we sort stocks into quintiles based on their β_X^i loadings estimated over the next 12 months, as in equation (3), and compute average returns over the same 12 months. Since we work in intervals of 12 months but evaluate annual returns at the monthly frequency, our research design employs overlapping information, which introduces moving average effects. To adjust for this, the reported t-statistics are computed using 12 Newey and West (1987) lags.[5] To ensure that our results are not driven by other factors or firm characteristics known to affect stock returns, we calculate abnormal returns (alphas) using the Fama and French (1993) three-factor model. The estimated abnormal return in the sorts is the constant α in the regression

$$R_t = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \varepsilon_t, \quad (4)$$

where R_t is the excess return over the risk-free rate to a quintile portfolio in year t, and MKT_t, SMB_t, and HML_t are, respectively, the excess return on the

[5] The theoretical number of lags required is 11 but, following Ang, Chen, and Xing (2006), we include a 12th lag for robustness.

market portfolio and the return on two long/short portfolios that capture size and book-to-market effects. Similarly, we run Fama–MacBeth regressions of 12-month excess returns on realized jump and volatility risk betas estimated over the same 12 months. Since the regressions are estimated at a 12-month horizon but at a monthly frequency, we again compute the standard errors of the coefficients by using 12 Newey–West (1987) lags. We use the results of Shanken (1992) to correct for the estimation noise in the first-step factor loading estimates.

B. Data Description

Our data on S&P 500 futures options come from the Chicago Mercantile Exchange (CME), where the contracts are traded. We focus on S&P 500 futures options rather than S&P 500 index options, because the former are more liquid and have historical data available over a longer sample period. The data set contains daily settlement prices on all call and put options on S&P 500 futures, along with daily settlement prices on the underlying futures contracts. The sample period for our analysis begins in January 1988, when the CME started trading one-month serial options on S&P 500 futures contracts, and ends in December 2011. The options are American, and contracts expire on the third Friday of each month. To filter possible data errors, we exclude any option prices that are lower than the immediate early exercise value. The stock return data in our cross-sectional tests come from CRSP. We include all stocks with an average price above one USD during the previous year.

Using S&P 500 futures options, we construct the jump and volatility risk–mimicking portfolios as described in Section I. The at-the-money market-neutral straddle returns that constitute our risk factors are computed daily as follows. At the close of trading on a given date, we pick the call and put option pair that is closest to being at-the-money among all options that expire in the next calendar month (for the short-dated options required in the strategies) and the calendar month that follows (for the long-dated options). We hold each position for one trading day, and thus pick new option pairs the next day.

Table I presents descriptive statistics on the JUMP and VOL factors. In addition, for comparison with prior work on aggregate volatility risk, we include descriptive statistics on straddle returns (as in Coval and Shumway (2001) and Driessen and Maenhout (2012)) and the CBOE VIX index (as in AHXZ). Market-neutral straddles (STR) are constructed from at-the-money options expiring in the next calendar month; the position is rebalanced daily to remain delta neutral.

Several observations emerge from the results in Table I. Both the JUMP and VOL factors earn significantly negative average returns (significant at the 1% and 5% level, respectively). Because the factors bear no market risk, by construction, this is an important result, as it suggests that some other factors are priced in option returns, namely, stochastic volatility and jump risk. The negative average returns of the JUMP and VOL factors are consistent with the prediction from economic theory of negative market prices for both

Table I
Summary Statistics for Volatility and Jump Risk Proxies

This table shows descriptive statistics (Panel A) and pairwise correlations (Panel B) for our volatility and jump risk factors at the daily frequency. The sample extends from January 1988 to December 2011. The JUMP risk factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The VOL risk factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy. Alternative proxies for volatility risk are STR (the market-neutral at-the-money straddle return following Coval and Shumway (2001)) and ΔVIX (the first difference in the CBOE VIX index following Ang et al. (2006)).

	Annualized Mean	Annualized SD	Annualized Sharpe Ratio	Daily Median	Skewness	Kurtosis
Panel A. Descriptive Statistics						
VOL	−0.0956	0.2418	−0.546	−0.0010	2.63	47.08
VOL Vega	180.01	88.155		181.87	0.24	2.06
JUMP	−0.4089	0.4811	−0.926	−0.0052	5.14	84.81
JUMP Gamma	0.0124	0.0089		0.0078	0.83	2.26
STR	−0.9667	1.0037	−0.999	−0.0143	8.30	181.43
ΔVIX	−0.6762	27.868		−0.0400	0.10	25.09

	VOL	JUMP	STR	ΔVIX
Panel B. Pairwise Correlations				
VOL	1.00			
JUMP	0.10	1.00		
STR	0.51	0.88	1.00	
ΔVIX	0.49	0.37	0.56	1.00

aggregate jump and aggregate volatility risk. The factor returns are volatile, skewed, and leptokurtic.[6] Table I also highlights the fact that the gamma of the JUMP factor and the vega of the VOL factor are not constant over time. Much of this time variation is mechanical: it is driven by changes in the level of the S&P 500 index and changes in volatility, and removing these effects leaves little residual variation.

Consistent with prior work (e.g., Coval and Shumway (2001) and Bakshi and Kapadia (2003)), we find that straddles earn negative average returns. The Sharpe ratios of the straddles are more negative than those of the JUMP and VOL factors, which suggests that the straddles are subject to both volatility and jump risk. The correlations in Panel B provide additional evidence in this regard. While the jump and volatility risk factors are essentially uncorrelated,

[6] In Table A.I of the Internet Appendix (the Internet Appendix may be found in the online version of this article), we investigate how the JUMP and VOL factors covary with realized variance and higher moment measures estimated from high-frequency returns. VOL is significantly correlated with realized semivariance (correlation of 0.28) and realized skewness (–0.24). JUMP shows expected correlations with realized skewness (–0.03) and kurtosis (0.07). While these correlations are small in magnitude, they are still significantly different from zero.

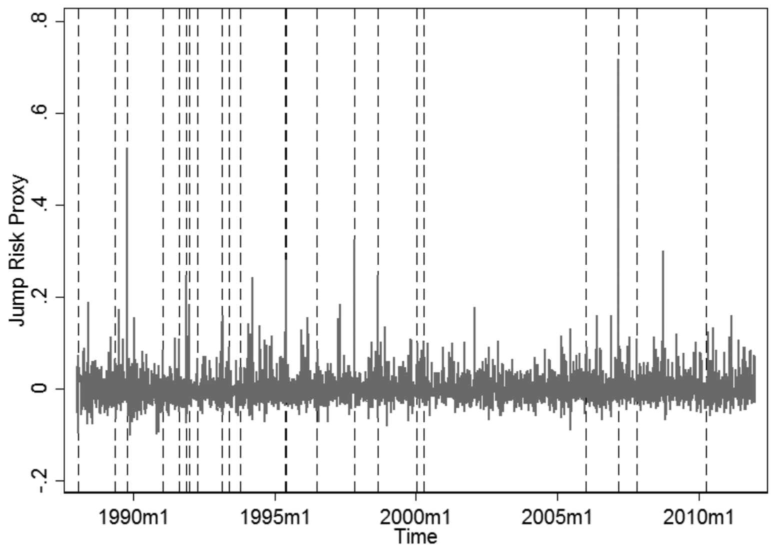

Figure 1. Time-series of daily returns on the JUMP factor. The figure shows the time-series of daily returns on the JUMP factor, which is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. Vertical dashed lines include realized jumps of the underlying S&P 500 index according to Lee and Mykland (2008). The sample period is from January 1988 to December 2011.

with a correlation of just 0.10, straddle returns have large positive correlations with both factors.

Innovations in the CBOE VIX index (ΔVIX) are also positively correlated with both the JUMP and the VOL factors. This finding is consistent with recent theoretical results in Du and Kapadia (2011) and Martin (2012) that suggest VIX is a biased measure of diffusion risk in the presence of jumps, with the degree of bias related to jump severity.[7]

Figure 1 shows the time-series of daily returns of the JUMP factor. The vertical lines indicate realized jumps in the S&P 500 index according to the Lee and Mykland (2008) nonparametric jump test. The JUMP strategy is constructed such that it has a positive return if the market's expectation of a jump in the S&P 500 increases. If the market's expectations correspond to realized jumps, we expect to see large positive JUMP factor returns when the Lee–Mykland test indicates a jump. This is precisely what we find in Figure 1.

[7] The standard interpretation of VIX is that it is a model-free measure of implied volatility. This follows from a series of papers, including Britten-Jones and Neuberger (2000), Carr and Madan (1998), Demeterfi et al. (1999), and Neuberger (1994), that derive a model-free implied volatility that equals the expected sum of squared returns under the risk-neutral measure, under few assumptions regarding the underlying stochastic process, except that there are no jumps. The dependence of VIX on higher moments is also discussed in Carr and Lee (2009). In reference to the financial crisis of 2008, they write that "dealers learned the hard way that the standard theory [...] is not nearly as model free as previously supposed [...] In particular, sharp moves in the underlying highlighted exposures to cubed and higher order daily returns" (p. 6).

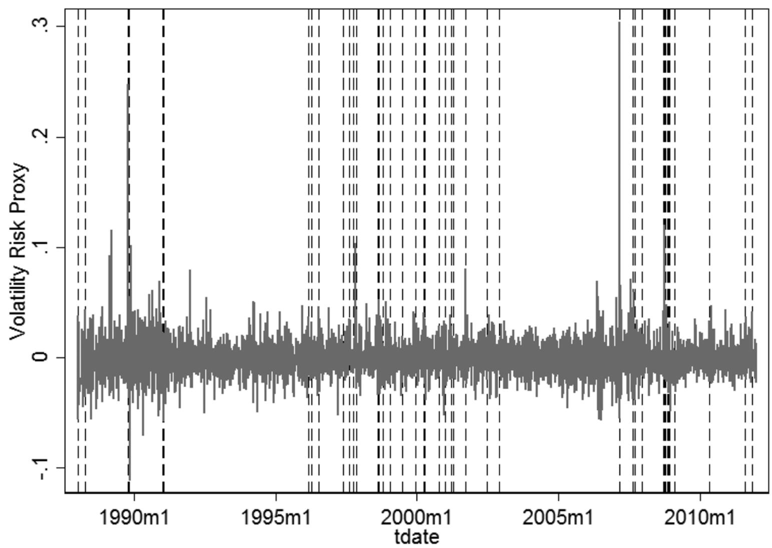

Figure 2. Time-series of daily returns on the VOL factor. The figure shows the time-series of daily returns on the VOL factor, which is the return on a market-neutral, gamma-neutral but vega-positive calendar spread option strategy. Vertical, dashed lines represent the 50 largest daily increases in realized volatility measured daily from five-minute returns. The sample period is from January 1988 until December 2011.

Similarly, Figure 2 shows the time-series of daily returns of the VOL factor. In this case, the vertical lines indicate the 50 largest increases in the daily realized standard deviation estimated from five-minute returns. The VOL strategy is constructed such that positive returns capture increases in the market's expectation of future market volatility. Thus, we expect to see that positive returns align well with vertical lines. Inspection of Figure 2 confirms this expectation.

Figures 1 and 2, however, are quite noisy, as they pertain to daily factor returns. Figure 3, in contrast, shows monthly returns of the VOL and JUMP factors. This figure reemphasizes several of the observations drawn from the summary statistics: the two factors are quite distinct and the jump risk factor is more volatile.

Finally, Figure 4, Panel A shows cumulative returns over the sample period. Most importantly, it illustrates the negative average returns of both strategies. As the cumulative returns of the JUMP factor converge quickly to –100%, we also show these returns in more detail for subperiods in Panel B (January 2000 to December 2006) and Panel C (January 2007 to December 2011).

The cumulative return graphs help identify aggregate time trends in jump and volatility risk. We observe extended periods during which these factors perform well (e.g., the end of the tech boom for the JUMP factor). We also find extended periods with consistently negative returns (and corresponding negative trends in the cumulative returns) for both risk factors (e.g., the period

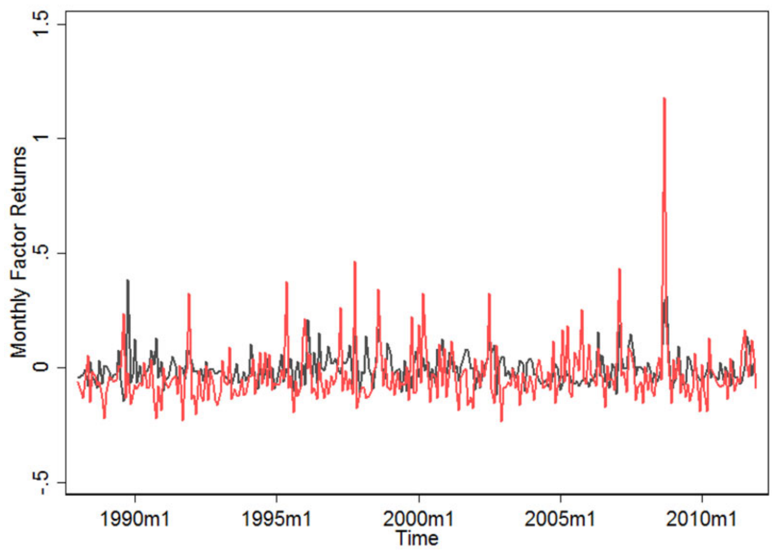

Figure 3. Monthly returns on VOL and JUMP factors. The figure shows the time-series of monthly returns on the VOL (black line) and the JUMP (red line) factors. The VOL factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy. The JUMP factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The sample period is from January 1988 to December 2011.

2004–2007 or the years after the recent financial crisis). These are periods during which the market assessment of jump and volatility risk decreased.

III. The Pricing of Jump and Volatility Risk

This section describes our main results on the pricing of jump and volatility risk in the cross-section of stock returns. We first present summary statistics on jump and volatility risk betas. We then discuss the results of portfolio sorts. Finally, we consider Fama–MacBeth regressions.

A. Summary Statistics for Jump and Volatility Betas

For each stock we estimate factor loadings at the individual stock level using daily returns over rolling annual horizons, as in regression (6). Panel A of Table II presents descriptive statistics on these factor loadings. Jump and volatility betas β_{JUMP} and β_{VOL} are close to zero on average and strongly leptokurtic (positive excess kurtosis). In the case of β_{VOL}, however, we observe more than twice as much cross-sectional variation than for β_{JUMP}.

Panel B shows the pairwise correlations of the factor loadings. Like the factors themselves, the jump and volatility factor loadings are almost uncorrelated, with a correlation of –0.029. In contrast, market neutral straddle betas and ΔVIX betas are positively correlated with both jump and volatility

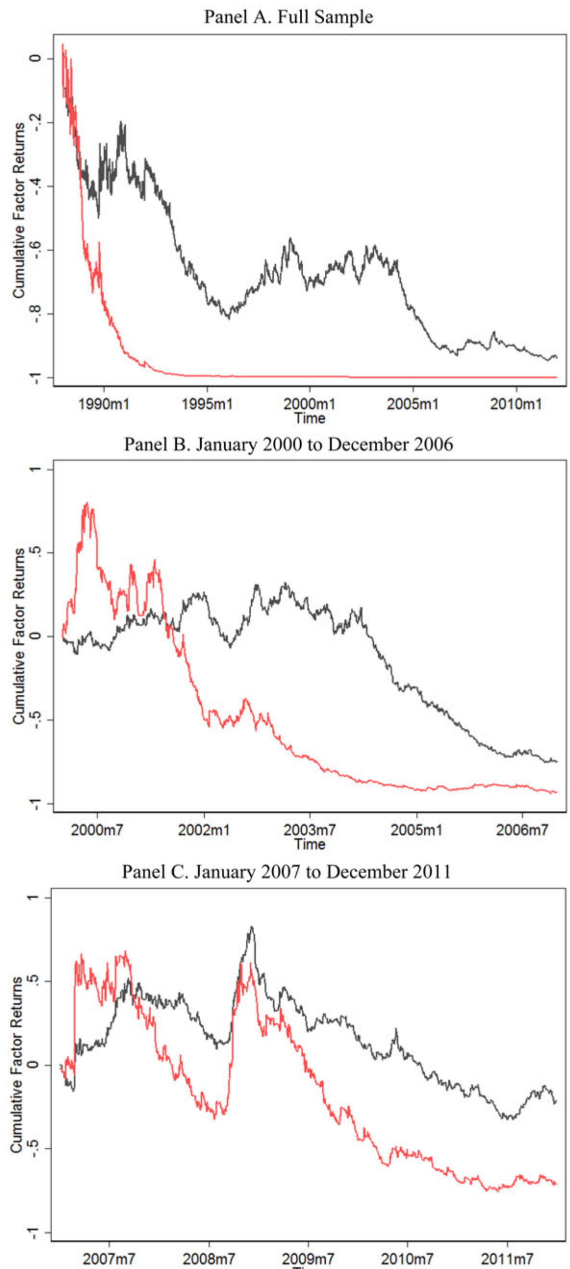

Figure 4. Cumulative daily returns on the VOL and JUMP factors. The figure shows cumulative daily returns on the VOL (black line) and the JUMP (red line) factors. The VOL factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy. The JUMP factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The sample period is from January 1988 to December 2011.

Table II

Summary Statistics for Volatility and Jump Risk Betas

This table shows time-series means of cross-sectional statistics (Panel A) and time-series means of pairwise correlations (Panel B) for firm betas. The sample extends from January 1988 to December 2011. Betas are estimated at the monthly frequency using daily data from the previous 12 months. The JUMP risk factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The VOL risk factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy. Alternative proxies for volatility risk are STR (the market neutral at-the-money straddle return following Coval and Shumway (2001)) and ΔVIX (the first difference in the CBOE VIX index following Ang et al. (2006)).

	Mean	SD	Skewness	Kurtosis
		Panel A. Descriptive Statistics		
β_{VOL}	0.001	0.335	0.879	35.459
β_{JUMP}	–0.014	0.155	0.146	27.926
β_{STR}	–0.006	0.081	0.418	23.138
$\beta_{\Delta\mathrm{VIX}}$	0.001	0.005	0.410	25.736
	β_{VOL}	β_{JUMP}	β_{STR}	$\beta_{\Delta\mathrm{VIX}}$
		Panel B. Pairwise Correlations		
β_{VOL}	1.000			
β_{JUMP}	–0.029	1.000		
β_{STR}	0.347	0.833	1.000	
$\beta_{\Delta\mathrm{VIX}}$	0.346	0.434	0.612	1.000

factor loadings, consistent with the view that straddle and ΔVIX betas reflect sensitivity to both jump and volatility risk.

B. Portfolio Sorts

In this section, we investigate whether aggregate jump and volatility risk are priced risk factors in the cross-section of stock returns through portfolio sorts. At the beginning of each 12-month period, we sort stocks into quintiles based on their realized betas with respect to the JUMP or the VOL factor over the next 12 months and compute average portfolio characteristics over the same 12 months (i.e., contemporaneously). While we focus on the results from value-weighted portfolios presented in Table III, for robustness Table IV reports the results of equally weighted portfolios.

For the jump risk factor, Panel A of Table III reports average returns, Fama–French three-factor alphas, and Sharpe ratios for value-weighted quintile portfolios and for a hedge portfolio that is long stocks with highest 20% (i.e., positive) loadings and short stocks with lowest 20% (i.e., negative) loadings, that is, going long quintile 5 and short quintile 1.

Several conclusions can be drawn from these results. First, stocks whose returns are more positively related to aggregate jump risk earn lower returns, consistent with our expectation that the market price of aggregate jump risk

Table III

Contemporaneous Characteristics of Value-Weighted Portfolios

Every month we create value-weighted portfolios by sorting stocks into quintiles based on their realized jump risk betas (β_{JUMP}; Panel A) and volatility risk betas (β_{VOL}; Panel B). The sample extends from January 1988 to December 2011. Betas are estimated over the previous 12 months. All reported portfolio characteristics are contemporaneous with the betas used to construct the portfolio and correspond to annual numbers. The portfolio characteristics are average returns, Fama–French three-factor alphas, Sharpe ratios and betas with respect to jump risk, volatility risk, and the Fama–French factors. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey–West lags.

Portfolio	Return	FF3-Alpha	Sharpe Ratio	β_{JUMP}	β_{VOL}	β_{MKT}	β_{SMB}	β_{HML}
Panel A. Characteristics of Portfolios Sorted by β_{JUMP}								
1 Low β_{JUMP}	0.253	0.133	0.983	−0.135	−0.001	1.082	0.357	−0.207
2	0.203	0.099	0.981	−0.054	−0.007	0.927	0.013	−0.013
3	0.189	0.090	0.957	−0.009	−0.011	0.913	−0.086	0.023
4	0.190	0.081	0.859	0.036	−0.008	0.991	−0.010	0.038
5 High β_{JUMP}	0.164	0.038	0.532	0.116	−0.011	1.249	0.077	−0.071
High−Low	−0.089	−0.094	−0.517	0.252	−0.010	0.167	−0.280	0.136
t-stat	−4.89	−4.44		23.84	−0.74	3.05	−3.73	1.33

Portfolio	Return	FF3-Alpha	Sharpe Ratio	β_{JUMP}	β_{VOL}	β_{MKT}	β_{SMB}	β_{HML}
Panel B. Characteristics of Portfolios Sorted by β_{VOL}								
1 Low β_{VOL}	0.239	0.104	0.895	0.005	−0.264	1.122	0.171	−0.046
2	0.203	0.097	1.004	0.002	−0.101	0.939	−0.090	0.045
3	0.183	0.084	0.905	0.002	−0.008	0.921	−0.117	0.044
4	0.185	0.084	0.827	−0.001	0.087	0.984	−0.045	−0.014
5 High β_{VOL}	0.193	0.077	0.668	0.002	0.260	1.012	0.230	−0.262
High−Low	−0.046	−0.027	−0.263	−0.003	0.525	0.101	0.059	−0.215
t-stat	−4.37	−2.40		−0.46	24.70	2.93	1.26	−2.27

is negative. A negative market price of risk implies that stocks with high sensitivities to innovations in aggregate market jump risk should earn low returns. This makes sense economically, as such stocks provide useful hedging opportunities for risk-averse investors, who dislike high systematic jump risk. Second, this empirical result is quite robust: the portfolio sorts show a monotonically decreasing pattern for all three performance measures and the differences between quintile portfolios 5 and 1 are statistically significant at the 1% level in each case. Third, jump risk appears to be important economically: the value-weighted long–short portfolio earns an average return of –8.9% per year (t-statistic –4.89); controlling for the three Fama–French factors results in an even larger average return of –9.4% per year (t-statistic –4.44). Fourth, the estimated annual market price of jump risk is quite close to the annualized time-series average of the JUMP factor return, as should be the case since the factor is tradable. Specifically, the estimated market price of jump risk in Table III is –8.9%/0.252 = –35.3%, which is quite close to the annualized mean JUMP factor return in Table I (–40.9%).

Table IV

Contemporaneous Characteristics of Equal-Weighted Portfolios

Every month we create equal-weighted portfolios by sorting stocks into quintiles based on their realized jump risk betas (β_{JUMP}; Panel A) and volatility risk betas (β_{VOL}; Panel B). The sample extends from January 1988 to December 2011. Betas are estimated over the previous 12 months. All reported portfolio characteristics are contemporaneous with the betas used to construct the portfolio and correspond to annual numbers. The portfolio characteristics are average returns, Fama–French three-factor alphas, Sharpe ratios and betas with respect to jump risk, volatility risk, and the Fama–French factors. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey–West lags.

Portfolio	Return	FF3-Alpha	Sharpe Ratio	β_{JUMP}	β_{VOL}	β_{MKT}	β_{SMB}	β_{HML}
Panel A. Characteristics of Portfolios Sorted by β_{JUMP}								
1 Low β_{JUMP}	0.152	0.017	0.555	−0.164	0.011	0.981	0.902	−0.250
2	0.149	0.025	0.668	−0.056	−0.004	0.809	0.581	−0.082
3	0.141	0.018	0.635	−0.001	−0.009	0.773	0.479	−0.035
4	0.130	0.002	0.528	0.037	−0.011	0.831	0.496	−0.041
5 High β_{JUMP}	0.093	−0.048	0.247	0.141	−0.012	1.044	0.726	−0.216
High−Low	−0.060	−0.065	−0.598	0.305	−0.023	0.063	−0.175	0.034
t-stat	−5.43	−4.85		25.48	−1.43	1.99	−3.50	0.54

Portfolio	Return	FF3-Alpha	Sharpe Ratio	β_{JUMP}	β_{VOL}	β_{MKT}	β_{SMB}	β_{HML}
Panel B. Characteristics of Portfolios Sorted by β_{VOL}								
1 Low β_{VOL}	0.143	0.004	0.492	−0.006	−0.323	0.986	0.806	−0.182
2	0.147	0.021	0.646	−0.007	−0.105	0.811	0.525	−0.038
3	0.138	0.017	0.625	−0.008	−0.008	0.776	0.476	−0.032
4	0.131	0.005	0.544	−0.011	0.090	0.831	0.549	−0.082
5 High β_{VOL}	0.106	−0.033	0.324	−0.019	0.322	1.034	0.828	−0.291
High−Low	−0.037	−0.036	−0.492	−0.013	0.645	0.049	0.022	−0.110
t-stat	−4.64	−4.43		−1.76	24.54	2.43	0.79	−2.09

Panel B of Table III presents the evidence for value-weighted portfolios of stocks sorted by their exposure to the aggregate volatility factor. Similar to the results regarding jump risk, we find significant differences between quintile portfolios 5 and 1. Consistent with the negative market price of risk found in AHXZ and in the option pricing literature (e.g., Bakshi, Cao, and Chen (2000), Pan (2002), and Eraker, Johannes, and Polson (2003), among others), stocks with high sensitivities to innovations in aggregate market volatility earn low returns. The rationale is again that such stocks provide useful hedging opportunities for risk-averse investors, who dislike high systematic volatility. The value-weighted long–short portfolio earns a raw return of –4.6% per year (*t*-statistic –4.37) and a risk-adjusted return of –2.7% per year (*t*-statistic –2.40). The estimated annual market price of volatility risk (–4.6%/0.525 = –8.8%) is quite close to the annualized time-series average of the VOL factor return (–9.6%). The return patterns across quintiles are monotonically decreasing for risk-adjusted returns, but not for raw returns and Sharpe ratios. In general, the results of the portfolio sorts suggest that aggregate volatility risk is priced in the cross-section but in a somewhat weaker way than jump risk.

Of course, showing that there is a relation between aggregate jump risk exposure and average returns does not rule out the possibility that the pattern is driven by other known cross-sectional determinants of expected returns. In addition to the performance measures, Table III also reports the contemporaneous risk exposure of the portfolios with respect to the Fama–French (1993) risk factors. Although we do not observe strictly monotonic patterns across quintile portfolios for these betas, we do find statistically significant spreads between the most extreme quintiles. Thus, it is important to control for sensitivities to these risk factors in a multivariate framework. We use Fama–MacBeth regressions for this purpose and discuss the corresponding results in the next section.

Finally, the portfolio sorts show that sorting on sensitivities to jump risk is very different from sorting on sensitivities to volatility risk. This is not surprising given the low correlations between the original risk factors JUMP and VOL and between betas with respect to these factors. For example, if we sort on jump risk betas, the spread in volatility risk betas between the top quintile portfolio and the bottom quintile portfolio is only –0.010 and statistically insignificant. For comparison, the corresponding spread in volatility risk betas if we sort on these betas themselves is 0.525.

So far, we have only discussed the results based on value-weighted portfolios. In a factor risk–based framework, a relationship between factor sensitivities and average returns should hold for both the average dollar and the average stock. In Table IV, we therefore examine the robustness of our results to forming equal-weighted rather than value-weighted portfolios. The evidence in Table IV is consistent with, and very similar to, the results based on value-weighted portfolios.

Table V further investigates the relation between JUMP betas and VOL betas by performing independent double sorts. Panel A of Table V shows the mean number of firms in each of the 25 corresponding portfolios. While the distribution of firms is relatively homogenous in general, portfolios in the corners and in the center of the matrix tend to have more firms on average. Panel B reports average raw returns for value-weighted portfolios. The corresponding 5–1 long–short portfolios show significant negative returns in all cases and, as expected with their low correlations, no strong patterns or interactions between volatility and jump risk exposures. The equal-weighted results in Panel C are again similar. Thus jump risk does not subsume volatility risk and volatility risk does not subsume jump risk.

C. Fama–MacBeth Regressions

The portfolio sorts present strong evidence that jump and volatility risk exposures are related to contemporaneous average stock returns. In addition, the average returns of the long–short portfolios further suggest negative market prices of risk for both jump and volatility risk, consistent with asset pricing

Table V

Average Returns of Stocks Sorted Independently by Realized Jump and Volatility Betas

Every month we create value-weighted (Panel B) and equal-weighted (Panel C) portfolios by independently sorting stocks into quintiles based on their realized jump risk betas (β_{JUMP}) and volatility risk betas (β_{VOL}). The sample extends from January 1988 to December 2011. Betas are estimated over the previous 12 months. All reported portfolio characteristics are contemporaneous with the betas used to construct the portfolio and correspond to annual numbers. Panel A reports the average number of firms in each portfolio. Panels B and C summarize contemporaneous average portfolio returns. Because we use overlapping returns and beta estimates, we adjust standard errors accordingly using 12 Newey–West lags.

Panel A. Average Number of Firms

	1 Low β_{VOL}	2	3	4	5 High β_{VOL}
1 Low β_{JUMP}	183	124	114	133	206
2	134	160	164	162	140
3	121	170	186	168	115
4	132	169	173	164	123
5 High β_{JUMP}	190	137	123	133	176

Panel B. Average Returns of Value-Weighted Portfolios

	1 Low β_{VOL}	2	3	4	5 High β_{VOL}	High−Low	t-stat
1 Low β_{JUMP}	0.281	0.275	0.249	0.239	0.237	−0.044	−2.05
2	0.260	0.210	0.192	0.198	0.205	−0.054	−2.47
3	0.231	0.196	0.189	0.185	0.187	−0.043	−2.11
4	0.242	0.204	0.178	0.168	0.194	−0.048	−2.36
5 High β_{JUMP}	0.211	0.173	0.141	0.160	0.174	−0.037	−1.88
High−Low	−0.070	−0.102	−0.108	−0.079	−0.063		
t-stat	−3.69	−4.67	−5.69	−4.05	−3.02		

Panel C. Average Returns of Equal-Weighted Portfolios

	1 Low β_{VOL}	2	3	4	5 High β_{VOL}	High−Low	t-stat
1 Low β_{JUMP}	0.162	0.169	0.161	0.153	0.130	−0.032	−3.72
2	0.167	0.158	0.149	0.143	0.126	−0.041	−4.68
3	0.163	0.150	0.141	0.134	0.115	−0.048	−5.91
4	0.145	0.143	0.132	0.122	0.107	−0.038	−4.39
5 High β_{JUMP}	0.096	0.110	0.103	0.100	0.067	−0.029	−3.23
High−Low	−0.066	−0.059	−0.058	−0.054	−0.063		
t-stat	−6.37	−5.75	−5.54	−4.58	−4.88		

theory. The portfolio sorts also reveal interactions between jump and volatility betas and the traditional Fama–French betas. These interactions are potentially important: while a factor-based model implies that there should be a contemporaneous pattern between factor loadings and average returns, making a case for a factor risk explanation also requires that the pattern be robust to other known determinants of returns. In this section, we begin to address

Table VI

Fama–MacBeth Regressions

This table investigates the cross-sectional pricing of aggregate jump and volatility risk. The sample period is from January 1988 to December 2011. We run Fama–MacBeth regressions of 12-month excess returns on contemporaneous realized betas. Observations are at the monthly frequency and we adjust standard errors accordingly using 12 Newey–West lags. The *t*-statistics, given between brackets below the coefficients, are also adjusted according to Shanken (1992) because betas are estimated. The JUMP factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The VOL factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy.

Model	1	2	3	4	5	6
JUMP	−0.166	−0.112			−0.170	−0.121
	[−3.80]	[−2.78]			[−4.24]	[−3.19]
VOL			−0.041	−0.043	−0.043	−0.042
			[−2.33]	[−2.96]	[−2.13]	[−2.37]
MKT	0.105	0.103	0.105	0.102	0.105	0.103
	[3.09]	[3.66]	[3.67]	[4.59]	[3.06]	[3.63]
SMB		0.018		0.019		0.017
		[0.93]		[1.24]		[0.90]
HML		0.011		0.009		0.009
		[0.98]		[1.07]		[0.82]
Intercept	0.074	0.072	0.075	0.073	0.073	0.072
	[3.66]	[4.13]	[3.72]	[4.17]	[3.64]	[4.12]

this issue by looking at the results from multivariate analyses using Fama–MacBeth regressions and the Fama–French factors. We consider additional factors and characteristics in Section IV when we investigate the robustness of our findings.

In the Fama–MacBeth analysis, we run two-step regressions of individual stock excess returns on realized betas with respect to the jump factor and the volatility factor. We continue to work with annual returns that we regress on the contemporaneously realized betas (which were obtained for each stock using daily data and estimated using the regression in equation (3)). As before, we are interested in contemporaneous effects.

The first two columns of Table VI show results from cross-sectional regressions of excess stock returns on the JUMP factor loading, β_{JUMP}, controlling only for the market return in Specification 1 and for the three Fama–French factors in Specification 2.

Several important implications emerge from this analysis. First, the Fama–MacBeth regressions confirm that jump risk is priced in the cross-section of returns and the market price of jump risk is negative. Second, this empirical result is robust across both regression specifications and consistent with the results from portfolio sorts. Third, the effect is economically important. To gauge the economic significance, we use the time-series mean of the cross-sectional standard deviations of β_{JUMP} reported in Panel A of Table II, namely, 0.155. Together with the estimated market risk premium of –0.166, this implies that a two-standard-deviation increase across stocks in β_{JUMP} is associated with a 5.1% drop in expected rate of return per annum ($-0.166 \times 2 \times 0.155 = -0.051$). The magnitude of this effect falls to –3.5% if we control for the Fama–French factors in the Fama–MacBeth regressions.

Specifications 3 and 4 analyze whether aggregate volatility risk is priced in the cross-section of stock returns. Consistent with the sorts, we again find that stocks with high sensitivities to innovations in aggregate market volatility earn low returns. To gauge the economic importance of aggregate volatility risk, we calculate the drop in expected rate of return that is associated with a two-standard-deviation increase across stocks in β_{VOL}. Given the time-series average of the cross-sectional standard deviation of β_{VOL} (0.335) reported in Panel A of Table II, the corresponding decrease in expected returns is 2.7%. This effect remains essentially unchanged if we control for the Fama–French factors in the Fama–MacBeth regressions.

An interesting byproduct of this analysis is that it enables us to estimate the economic effects of jump and volatility risk controlling for both types of risk at the same time. Specifications 5 and 6 report the corresponding results. We find that the estimated market risk premiums are very similar to those estimated in Specifications 1 to 4. This is important because it suggests that aggregate jump and volatility risk are priced separately in the cross-section and that our proxies successfully distinguish between these different types of risk.

Overall, the evidence we uncover on the pricing of jump and volatility risk in the cross-section of stock returns suggests that both sources of risk are important. Comparing the economic magnitudes of the estimated market risk premiums and the performance of the long–short portfolios, we find that systematic jump exposure matters as much as, if not more than, aggregate volatility exposure. Thus, our results on the cross-sectional pricing of aggregate jump risk are in line with the results in the related time-series literature, which suggests that time-varying aggregate jump risk has a substantial effect on aggregate market returns (e.g., Santa-Clara and Yan (2010)).

IV. Extensions

This section describes several extensions of our basic analysis in Section III. First, we consider a battery of robustness tests including controls for size, book-to-market, illiquidity, downside and upside beta, conditional skewness and kurtosis, idiosyncratic volatility, idiosyncratic skewness, the variance risk premium, the realized standard deviation, and risk-neutral skewness and kurtosis. Second, we examine whether our results on the pricing of aggregate jump and volatility risk are robust to the use of alternative nontradable but theoretically motivated jump and volatility proxies, as well as to using market-neutral straddle returns and changes in VIX as alternative volatility proxies. Third, we investigate whether we can predict future jump and volatility risk betas.

A. Robustness of the Pricing of Jump and Volatility Risk

In this subsection, we investigate whether the contemporaneous relation between jump and volatility risk loadings and returns is robust to the inclusion of several control variables. The control variables that we consider are factor loadings with respect to momentum, firm size, book-to-market, illiquidity (as in Amihud (2002)), downside beta (as in Ang, Chen, and Xing (2006)), conditional skewness (as in Harvey and Siddique (2000)), and conditional kurtosis (as in Dittmar (2002)), idiosyncratic volatility (as in Ang et al. (2006)), idiosyncratic skewness (as in Boyer, Mitton, and Vorkink (2010)), the variance risk premium (as in Bollerslev, Tauchen, and Zhou (2009)), the realized standard deviation, and risk-neutral skewness and kurtosis (as in Bakshi, Kapadia, and Madan (2003) and Duan and Wei (2009)).

The momentum factor is taken from Ken French's website and firm betas are estimated using daily returns over rolling annual periods, following equation (3). Book equity, calculated at the quarterly frequency using Compustat, is defined as stockholders' equity plus deferred taxes and investment tax credit minus preferred capital. If this calculation yields a missing value, we replace it with the difference between total assets and total liabilities. The illiquidity measure corresponds to the Amihud ratio and is calculated at the daily frequency as the ratio of absolute return to trading volume. We compute downside beta as the sample counterpart of the measure introduced in Bawa and Lindenberg (1977), namely,

$$\beta^{i-} = \frac{\mathrm{cov}(R_t^i, MKT_t | MKT_t < \mu^{MKT})}{\mathrm{var}(MKT_t | MKT_t < \mu^{MKT})}, \tag{5}$$

where μ^{MKT} is the sample average market return. We calculate conditional skewness as the sample counterpart of the measure

$$CSKEW = \frac{\mathrm{E}\left(\left(R_t^i - \mu^i\right) \cdot \left(MKT_t - \mu^{MKT}\right)^2\right)}{\sqrt{\mathrm{var}\left(R_t^i\right)} \cdot \mathrm{var}\left(MKT_t\right)},$$

where μ^i is the average excess return on the stock. Conditional kurtosis is defined analogously. We compute idiosyncratic volatility and idiosyncratic skewness relative to the Fama–French three-factor model, defining them as the standard deviation and skewness of ε_t in the regression

$$R_t = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \varepsilon_t. \tag{6}$$

The variance risk premium is defined as the difference between VIX and realized variance. We also consider the ex post variance risk premium, which uses lagged VIX. Daily estimates of the realized standard deviation of the S&P 500 are downloaded from the data library of the Oxford-Man Institute of Quantitative Finance for the sample period starting in January 2000. For earlier years, we estimate the realized standard deviation ourselves using five-minute returns obtained from Tick Data, Inc. Finally, risk-neutral skewness and kurtosis are estimated from the cross-section of option prices at the daily frequency.

Panels A and B of Table VII show the distribution of these control variables across value-weighted quintile portfolios of stocks sorted by β_{JUMP} (Panel A) and β_{VOL} (Panel B).[8] As before, we sort stocks into quintiles based on their realized betas with respect to the JUMP or the VOL factor over the next 12 months and then compute averages of the control variables over the same 12 months. In the case of portfolio sorts based on jump risk betas, we find monotonic patterns across these portfolios for momentum beta (decreasing), illiquidity (decreasing), upside beta (increasing), conditional skewness (increasing), variance risk premium beta (decreasing), realized standard deviation beta (increasing), and risk-neutral skewness beta (increasing). In the case of portfolio sorts based on volatility risk betas, we observe monotonic patterns for variance risk premium beta (decreasing), realized standard deviation beta (increasing), and risk-neutral skewness beta (increasing).

In both panels, however, we find significant 5–1 spreads for several control variables. Overall, the portfolio sorts suggest interesting cross-sectional interactions between jump and volatility risk and these control variables. Because these effects may be at play in the results of Section III, it is important to verify that jump and volatility risk are also priced in the cross-section of stock returns when we control for these additional risk factors in a multivariate framework.

Panel C of Table VII reports the results from Fama–MacBeth regressions. To keep the table tractable, we focus on the estimated market risk premiums associated with jump and volatility risk. All specifications include the three Fama–French factors. The evidence shows that our results on the pricing of aggregate jump and volatility risk are remarkably robust: the estimated market prices of volatility and jump risk are very stable across the various specifications and all the Shanken (1992) t-statistics remain significant. Only in the specifications in which we control for downside beta and conditional skewness do we observe a slight drop in the market risk premium of jump risk. This is perhaps not too surprising, as downside beta and conditional skewness are both associated, to some extent, with the notion of jump risk. Nevertheless, our jump beta risk is different from both downside beta risk and conditional skewness.[9] The consistent message from the regressions in Table VII is that reward for bearing jump risk and volatility risk is always negative, remarkably stable, and statistically significant.

[8] The results for equal-weighted portfolios in Table A.II of the Internet Appendix are very similar.

[9] As an additional robustness test, we regress our factors on the Harvey and Siddique (2000) skewness factor to strip out skewness and on up- and down-market returns to strip out asymmetric beta. Completely removing these effects from our factors leaves the results largely unchanged; we observe slightly smaller market prices of risk in absolute terms and negligible reductions in significance levels.

Table VII

Robustness Tests

This table investigates the robustness of the cross-sectional pricing of aggregate jump and volatility risk. The sample period is from January 1988 to December 2011. Panels A and B report results from portfolio sorts. Every month we create value-weighted portfolios by sorting stocks into quintiles based on their realized jump risk betas (β_{JUMP}; Panel A) and volatility risk betas (β_{VOL}; Panel B). Betas are estimated over the previous 12 months. All reported portfolio characteristics are contemporaneous with the betas used to construct the portfolio. In Panel C we estimate Fama–MacBeth regressions of 12-month excess returns on contemporaneous realized betas and firm characteristics. More specifically, we repeat specifications 2, 4, and 6 from Table VI but add a battery of robustness variables. For readability the table only reports estimates of jump and volatility market risk premia. The additional controls included in Panels A–C are sensitivity to momentum (MOM), market capitalization (MC), book-to-market (B/M), illiquidity (ILLIQ, the Amihud measure multiplied by 1,000), downside and upside beta (Asym. Beta), conditional skewness, conditional kurtosis, idiosyncratic volatility (Idio. Vola), idiosyncratic skewness (Idio. Skew), variance risk premium (spread between implied volatility and realized volatility), ex post variance risk premium (the spread between lagged implied volatility and realized volatility), realized standard deviation, risk-neutral skewness, and risk-neutral kurtosis. Observations are at the monthly frequency and we adjust standard errors accordingly using 12 Newey–West lags. The t-statistics in Panel C are also adjusted according to Shanken (1992).

Panel A. Robustness Characteristics of Portfolios Sorted by β_{JUMP}

Portfolio	1 Low β_{JUMP}	2	3	4	5 High β_{JUMP}	High−Low	t-stat
β_{MOM}	0.065	0.016	−0.008	−0.003	−0.172	−0.237	−3.89
MC	3.440	5.170	5.570	5.570	4.020	0.580	1.33
B/M	0.483	0.503	0.465	0.509	0.496	0.013	0.56
ILLIQ	0.606	0.534	0.406	0.319	0.318	−0.288	−1.96
$\beta_{\mathrm{MKT-}}$	1.241	0.998	0.928	0.942	1.072	−0.167	−2.93
$\beta_{\mathrm{MKT+}}$	0.789	0.835	0.925	1.087	1.418	0.629	11.99
Cond–Skew	−0.213	−0.176	−0.133	−0.088	−0.036	0.177	15.29
Cond–Kurt	2.219	2.469	2.564	2.604	2.444	0.225	2.24
Idio–Vola	0.023	0.017	0.015	0.016	0.021	−0.002	−2.87
Idio–Skew	−0.255	−0.225	−0.178	−0.181	−0.287	−0.033	−0.93
VRP	0.013	0.003	−0.002	−0.007	−0.020	−0.032	−4.72
VRP–Post	0.018	0.006	−0.001	−0.008	−0.025	−0.044	−5.81
Realized SD	−0.028	−0.011	0.000	0.011	0.036	0.064	7.97
RN–Skew	−0.007	−0.004	−0.002	0.001	0.008	0.016	2.71
RN–Kurt	0.002	0.001	0.000	0.000	−0.002	−0.003	−2.64

Panel B. Robustness Characteristics of Portfolios Sorted by β_{VOL}

Portfolio	1 Low β_{VOL}	2	3	4	5 High β_{VOL}	High−Low	t-stat
β_{MOM}	0.012	0.021	−0.020	−0.028	−0.059	−0.071	−1.04
MC	3.450	5.270	6.030	5.540	3.650	0.200	0.52
B/M	0.466	0.497	0.473	0.496	0.534	0.069	1.14
ILLIQ	0.635	0.355	0.361	0.382	0.362	−0.273	−2.08
$\beta_{\mathrm{MKT-}}$	1.126	0.943	0.918	0.973	1.176	0.050	1.52
$\beta_{\mathrm{MKT+}}$	1.066	0.962	0.968	1.017	1.193	0.127	3.56
Cond–Skew	−0.131	−0.134	−0.122	−0.114	−0.100	0.032	2.71
Cond–Kurt	2.351	2.570	2.620	2.508	2.275	−0.076	−1.01

(Continued)

Table VII—*Continued*

Panel C. FM Regressions Including Additional Controls

Robustness	Added to Model 2, Table 6		Added to Model 4, Table 6		Added to Model 6, Table 6			
	β_{JUMP}		β_{VOL}		β_{JUMP}		β_{VOL}	
Variable	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
MOM	−0.091	−2.34	−0.032	−2.30	−0.094	−2.54	−0.032	−1.81
MC	−0.114	−2.79	−0.042	−2.88	−0.122	−3.19	−0.040	−2.29
B/M	−0.112	−2.46	−0.042	−2.48	−0.149	−3.60	−0.033	−1.84
ILLIQ	−0.118	−2.49	−0.040	−2.22	−0.156	−3.81	−0.035	−2.00
Asym. Beta	−0.073	−1.80	−0.040	−2.81	−0.082	−2.14	−0.038	−2.11
Cond. Skew + Cond. Kurt.	−0.073	−1.96	−0.034	−2.46	−0.083	−2.35	−0.032	−1.77
Idio. Vola	−0.115	−3.03	−0.039	−2.95	−0.126	−3.55	−0.037	−2.35
Idio. Skew	−0.093	−2.57	−0.038	−3.01	−0.100	−2.87	−0.037	−2.33
VRP	−0.146	−3.21	−0.037	−2.20	−0.166	−3.96	−0.035	−2.08
VRP-Post	−0.148	−3.26	−0.036	−2.12	−0.169	−4.19	−0.037	−2.11
Realized SD	−0.089	−2.01	−0.032	−1.93	−0.114	−2.79	−0.031	−1.80
RN–Skew + RN–Kurt	−0.101	−1.99	−0.037	−1.97	−0.139	−3.27	−0.036	−1.87

B. Alternative Proxies for Jump and Volatility Risk

Next, we investigate whether our results on the pricing of aggregate jump and volatility risk are robust to the use of alternative nontradable but theoretically motivated jump and volatility proxies. Two theoretical results guide our empirical design.

First, in a continuous-time jump diffusion model, Yan (2011) proposes the change in the slope of the implied volatility smirk as the right proxy for jump risk, as the smirk is approximately proportional to the product of the jump intensity parameter and the jump size in his model. Thus, our smirk measure (ΔIV-Smirk) is the difference between the implied volatility of an out-of-the-money put option (0.95 strike-to-spot ratio) and an at-the-money call option.[10]

Second, Du and Kapadia (2011) show that VIX is a biased estimator of volatility in the presence of price discontinuities, which makes it difficult to accurately distinguish between volatility and jump risk. The key insight in Du and Kapadia (2011) is that the bias in VIX is proportional to the jump intensity. Because time-variation in jump intensity determines time-variation in jump risk, a jump index can be constructed based on the degree to which VIX inaccurately measures volatility. Of course, this requires that a more accurate measure of volatility be constructed. Du and Kapadia (2011) show that, while both VIX and the Bakshi, Kapadia, and Madan (2003) measure of the variance

[10] There is evidence that volatility smirks become more pronounced around large jumps (e.g., Bates (1991)). Du (2011) shows within an option pricing model that time-varying investor risk aversion due to jumps is the driving force behind volatility smirks.

Table VIII

Results of FM Regressions Using Alternative Risk Proxies

This table reports results from Fama–MacBeth regressions using alternative proxies for volatility risk and jump risk. The sample period is from January 1988 to December 2011. We run Fama–MacBeth regressions of 12 month excess returns on contemporaneous realized betas. Observations are at the monthly frequency and we adjust standard errors accordingly using 12 Newey–West lags. The JUMP factor is the return on a market-neutral, vega-neutral, but gamma-positive calendar spread option strategy. The VOL factor is the return on a market-neutral, gamma-neutral, but vega-positive calendar spread option strategy. In Panel A, the alternative jump risk proxies are ΔIV-Smirk (daily change in the implied volatility smirk following Yan (2011)) and ΔJumpIndex (daily change in the tail index defined in Du and Kapadia (2011)). The alternative proxy for volatility risk is ΔVol-BKM (the change in the Bakshi, Kapadia, and Madan (2003) measure of volatility). Panel B shows results using market-neutral at-the-money straddle returns (STR; following Coval and Shumway (2001)) and changes in VIX (ΔVIX; following Ang et al. (2006)). Observations are at the monthly frequency and we adjust standard errors accordingly using 12 Newey-West lags. The *t*-statistics of coefficients from Fama–MacBeth regressions, given between brackets below the coefficients, are also adjusted according to Shanken (1992).

Panel A. Alternative Jump and Volatility Risk Proxies

Model	1	2	3	4	5	6
ΔVol-BKM	−3.595	−2.108				
	[−2.35]	[−0.92]				
ΔJumpIndex			−0.109	−0.129		
			[−1.05]	[−0.85]		
ΔIV-Smirk					−0.008	−0.009
					[−2.34]	[−1.92]
JUMP		−0.138		−0.140		−0.143
		[−3.11]		[−3.18]		[−3.05]
VOL		−0.035		−0.036		−0.038
		[−1.80]		[−1.85]		[−1.75]
MKT	0.102	0.105	0.102	0.105	0.102	0.104
	[4.55]	[3.37]	[4.67]	[3.41]	[4.23]	[3.08]
SMB	0.019	0.017	0.020	0.018	0.023	0.022
	[1.24]	[0.81]	[1.28]	[0.84]	[1.42]	[0.97]
HML	0.010	0.006	0.011	0.007	0.013	0.009
	[1.17]	[0.53]	[1.22]	[0.55]	[1.36]	[0.71]
Intercept	0.073	0.081	0.073	0.080	0.085	0.091
	[4.18]	[4.75]	[4.18]	[4.72]	[4.65]	[5.13]

Panel B. Using Straddle Returns and Changes in VIX

Model	1	2	3	4
HML	0.010	0.007	0.010	0.007
	[0.85]	[0.48]	[1.20]	[0.62]
Intercept	0.072	0.080	0.073	0.080
	[4.12]	[4.72]	[4.17]	[4.71]

of the holding period return are biased for general classes of jump diffusions, the bias in VIX is much larger. Following Du and Kapadia (2011), we therefore construct a jump index as the difference between the Bakshi, Kapadia, and Madan (2003) measure of volatility and the VIX measure.[11] We then use the jump index (ΔJumpIndex) along with the Bakshi, Kapadia, and Madan (2003) volatility measure (ΔVol-BKMV) in the asset pricing tests.

The evidence in Panel A of Table VIII shows that our results on the pricing of volatility and jump risk are quite robust to the use of these alternative nontradable measures. The volatility risk measure ΔVol-BKMV and the jump risk measure ΔIV-Smirk carry a negative and statistically significant market price of risk (see Models 1 and 5). Only in the case of the jump index ΔJumpIndex is its estimated negative market risk premium statistically insignificant (Model 3). This lack of statistical significance may be due to estimation noise induced by the discrete approximation of a continuum of strike prices. Overall, we conclude that these results are similar to, but weaker than, our main results, which are based on readily tradable option strategies to capture jump and volatility risk.

If we run a horse race between these alternative proxies and our main factors, we find several interesting results. The effect of ΔVol-BKMV exposures, an alternative measure of sensitivity to volatility risk, becomes insignificant once we also control for JUMP and VOL betas (see Model 2). This is not surprising and confirms that our main factors do a good job of capturing volatility risk. The sensitivities to ΔIV-Smirk are marginally significant if we control for JUMP and VOL betas (Model 6). Thus, it seems that ΔIV-Smirk captures a different, potentially more asymmetric, aspect of jump risk.

Finally, for comparison with prior work on aggregate volatility risk, we also include the results of Fama–MacBeth regressions using sensitivities with respect to standard market-neutral straddle returns (STR) and simple changes in VIX (ΔVIX). Results are presented in Panel B of Table VIII. In both cases we find negative prices of risk that are highly significant and economically large (Models 1 and 3). The betas, however, are more difficult to interpret because the underlying proxies are affected by both jump and volatility risk. As we argue in Section I, market-neutral straddle returns are sensitive to both volatility and jump risk. Similarly, Du and Kapadia (2011) show that VIX is a biased estimator of volatility in the presence of price discontinuities, which makes it difficult to accurately distinguish between volatility and jump risk using VIX.

[11] The construction of both the VIX index and the Bakshi, Kapadia, and Madan (2003) volatility measure requires a continuum of strike prices. Following Du and Kapadia (2011) and Jiang and Tian (2005), we interpolate the implied volatilities across the range of observed option prices using a cubic spline and assume the smirk to be flat beyond this range. We then compute 1,001 option prices using the interpolated curve over a range of zero to three times the underlying futures price. We follow this procedure for options that expire in the current month and in the next month, thus constructing two curves, and then create a 30-day implied volatility curve by linear interpolation across the two near-month implied volatility curves.

Table IX

Average Returns of Stocks Sorted by Past Jump and Volatility Betas

Every month we create equal-weighted (EW) and value-weighted (VW) portfolios by sorting stocks into quintiles based on their realized jump risk betas (β_{JUMP}) and volatility risk betas (β_{VOL}). The sample period is from January 1988 to December 2011. Betas are estimated over the previous 12 months. Then we calculate portfolio returns over the following 12 months and report average future returns and Sharpe ratios for these quintile portfolios and for a 5–1 long–short portfolio. We also include Fama–French alphas for the 5–1 portfolios. Because we use overlapping returns, we adjust all standard errors accordingly using 12 Newey–West lags. The t-statistics, given between brackets below the coefficients, are also adjusted according to Shanken (1992) because betas are estimated.

	JUMP Betas β_{JUMP}				Volatility Betas β_{VOL}			
	EW		VW		EW		VW	
Portfolio	Returns	Sharpe Ratios	Returns	Sharpe Ratios	Returns	Sharpe Ratios	Returns	Sharpe Ratios
1 Low $\beta_{(t-12)}$	0.086	0.332	0.075	0.240	0.096	0.403	0.099	0.380
2	0.101	0.460	0.080	0.308	0.108	0.498	0.099	0.414
3	0.107	0.510	0.096	0.412	0.106	0.494	0.092	0.372
4	0.108	0.498	0.096	0.374	0.103	0.471	0.093	0.357
5 High $\beta_{(t-12)}$	0.100	0.421	0.100	0.329	0.088	0.356	0.085	0.257
High−Low	0.014	0.274	0.025	0.200	−0.008	−0.189	−0.013	−0.110
	[4.57]		[3.34]		[−3.14]		[−1.83]	
High−Low	0.011		0.017		−0.005		−0.009	
FF3-Alpha	[3.59]		[2.33]		[−1.65]		[−1.83]	

We find strong evidence that market-neutral straddles capture both volatility and jump risk in Model 2, where we include STR together with JUMP and VOL, which renders all three risk factors insignificant. Model 4 suggests the same but to a lesser extent for ΔVIX, which becomes insignificant when JUMP and VOL are included as well, with JUMP remaining statistically significant but VOL also becoming insignificant (Model 4).

C. Predicting Future Jump and Volatility Risk

The results we discuss so far focus on contemporaneous relations between aggregate jump and volatility risk loadings and firm returns. While we find strong evidence that jump and volatility risk are priced in the cross-section of stock returns, this contemporaneous analysis may be of limited practical use, as it does not reflect an ex ante implementable strategy that can be followed to construct hedge portfolios. Thus, we study whether future jump and volatility risk loadings can be predicted in this section.

As a first step, we examine whether simply sorting stocks on past jump/volatility risk loadings provides enough variation in future jump/volatility risk to produce spreads in future returns. For this purpose, we sort stocks into quintiles based on their realized betas with respect to the JUMP or the VOL factor over the past 12 months (t – 11, t) and then compute average returns over the next 12 months (t + 1, t + 12). Table IX reports the results.

For portfolios sorted on volatility risk, we find results that are consistent with the contemporaneous sorts. Focusing on value-weighted portfolios again, we find a nearly monotonically decreasing pattern of returns with a significantly negative average return for the 5–1 hedge portfolio. Although the negative returns are smaller than those found for contemporaneous sorts, they are still significant.

In contrast, in the case of portfolios sorted on jump risk, we observe a surprisingly strong return reversal: the average return and the Fama–French three-factor alpha of a long–short portfolio that buys the top-quintile portfolio and shorts the bottom-quintile portfolio are significantly positive. This indicates that the jump risk loadings are strongly time-varying, such that simply using past loadings does not result in consistent exposures to jump risk. In response, we test if we can construct investable portfolios with a spread in jump risk loadings by using past information to explicitly predict future jump risk betas. Specifically, we run Fama–MacBeth regressions in which we regress jump risk betas estimated over $(t + 1, t + 12)$ on a set of firm characteristics including size, the Fama–French betas, and other risk controls[12] known at time t. Table X summarizes the corresponding results.

In univariate specifications, jump risk betas have statistically significant but economically small positive autocorrelations. This confirms that simply using past jump betas to predict future jump betas is difficult because past jump betas are poor predictors of future jump betas, consistent with our finding in Table IX that a naive strategy of sorting stocks on past jump betas alone is not effective. Furthermore, size, upside beta, conditional skewness, conditional kurtosis, idiosyncratic skewness, and realized standard deviation beta all predict future jump risk betas with statistically significant positive coefficients; illiquidity, idiosyncratic volatility, and variance risk premium betas receive significantly negative coefficients. Table X also reports a kitchen-sink regression in which we include all the lagged firm characteristics at the same time. The results are broadly consistent with those from the univariate specifications, although some coefficients lose significance. Overall, it seems that firm size, asymmetric market betas, conditional skewness, idiosyncratic volatility, and realized standard deviation betas robustly predict future jump risk loadings.

These lead–lag relations between firm characteristics and jump risk betas, however, do not necessarily imply that investors could use the predicted values to construct hedge portfolios in a successful way. To address this issue, we evaluate portfolio sorts in which we sort stocks with respect to predicted jump risk betas. We use the kitchen-sink regression (i.e., the column labeled "Multivariate Model" in Panel A of Table X) to compute the predicted jump risk loading for each firm. Panel B of Table X shows realized future jump risk betas, raw returns, and Sharpe ratios of quintile portfolios based on these predicted jump risk loadings, as well as those of a long–short portfolio that

[12] We consider all variables included in the robustness tests except for the ex post variance risk premium. The reason is that we cannot include both the variance risk premium and the ex post variance risk premium in the multivariate specification due to multicollinearity issues.

Table X

Predicting Future Jump Risk Loadings

Panel A summarizes results of Fama–MacBeth regressions in which we regress jump risk betas estimated over $(t+1, t+12)$ on firm characteristics known at time t. The sample period is from January 1988 to December 2011. Firm characteristics include jump risk beta, volatility risk beta, Fama–French SMB and HML beta, momentum beta, market capitalization, book-to-market (B/M), illiquidity (ILLIQ, the Amihud measure multiplied by 1,000), downside beta, upside beta, conditional skewness, conditional kurtosis, idiosyncratic volatility, idiosyncratic skewness, variance risk premium (spread between implied volatility and realized volatility), realized standard deviation, risk-neutral skewness, and risk-neutral kurtosis. The column labeled "Univariate Models" contains coefficient estimates of regressions in which we include each firm characteristic individually or pairwise (in the case of downside and upside beta, conditional skewness and kurtosis, and risk-neutral skewness and kurtosis). The last column reports coefficient estimates in a specification in which we control for all characteristics simultaneously. Panel B reports results from portfolio sorts. Every month we create equal-weighted (EW) and value-weighted (VW) portfolios by sorting stocks into quintiles based on their predicted jump risk betas (using the multivariate specification of Panel A). Then we report average future returns and average future realized jump risk betas for these quintile portfolios and for a 5–1 long–short portfolio. We also include Fama–French alphas for the 5–1 portfolios. Because we use overlapping returns, we adjust all standard errors accordingly using 12 Newey-West lags.

Panel A. FM Regressions Predicting β_{JUMP}

Model	Univariate Models	Multivariate Model
β_{JUMP} $(t-12)$	0.027	0.003
	[4.29]	[0.59]
β_{VOL} $(t-12)$	−0.001	0.001
	[−0.32]	[0.26]
β_{SMB} $(t-12)$	0.097	−0.546
	[0.42]	[−2.37]
β_{HML} $(t-12)$	−0.255	−0.144
	[−1.24]	[−0.91]
β_{MOM} $(t-12)$	−0.151	0.681
	[−0.48]	[2.16]
MC $(t-12)$	0.000	0.000
	[6.79]	[3.44]
B/M $(t-12)$	−0.001	0.001
	[−0.71]	[0.84]
ILLIQ $(t-12)$	−0.540	0.152
	[−2.32]	[0.94]
$\beta_{\mathrm{MKT}-}$ $(t-12)$	0.013	0.772
	[0.07]	[4.46]
$\beta_{\mathrm{MKT}+}$ $(t-12)$	1.059	0.705
	[4.41]	[2.39]
Cond. Skew. $(t-12)$	0.021	0.012
	[3.88]	[2.12]
Cond. Kurt. $(t-12)$	0.010	−0.001
	[5.77]	[−0.41]
Idio. Vola $(t-12)$	−0.335	−0.596
	[−2.92]	[−8.33]
Idio. Skew $(t-12)$	0.001	0.000
	[2.82]	[1.05]
VRP $(t-12)$	−0.071	0.006

(Continued)

Table X—*Continued*

Model	Univariate Models	Multivariate Model
	[−3.59]	[0.74]
Realized SD (t − 12)	0.063	0.034
	[4.95]	[4.07]
RN-Skew (t − 12)	0.069	−0.025
	[1.34]	[−0.65]
RN-Kurt (t − 12)	0.045	−0.285
	[0.13]	[−1.08]

Panel B. Portfolio Sorts Based on Predicted Jump Risk Loadings

	Future Realized β_{JUMP}		Future Avg. Returns		Future Sharpe Ratios	
Portfolio	EW	VW	EW	VW	EW	VW
1 Low predicted β	−0.018	−0.021	0.129	0.196	0.446	0.714
2	−0.013	−0.017	0.126	0.184	0.483	0.786
3	−0.008	−0.010	0.120	0.163	0.476	0.776
4	−0.005	−0.006	0.115	0.152	0.459	0.804
5 High predicted β	0.006	0.007	0.096	0.131	0.330	0.585
High−Low	0.024	0.028	−0.033	−0.064	−0.280	−0.352
	[6.08]	[7.03]	[−2.41]	[−3.13]		
High−Low			−0.014	−0.018		
FF3-Alpha			[−1.93]	[−2.02]		

buys stocks in quintile 5 and shorts stocks in quintile 1. Consistent with the contemporaneous results, we find a strong negative and monotonic relation between predicted jump risk betas and average returns. The average annualized value-weighted return of the long–short portfolio is –6.4% with a Newey–West adjusted t-statistic of –3.13. The Fama–French risk-adjusted return is smaller but remains significant. As one would expect, realized future jump risk betas of these portfolios increase monotonically resulting in a significant 5–1 spread of 0.028. We find similar results for equal-weighted portfolios.

V. Conclusion

This paper introduces measures of jump and volatility risk that are constructed from index options to examine the pricing of aggregate jump and volatility risk in the cross-section of stock returns. The jump and volatility factor-mimicking portfolios are directly tradable strategies that we construct explicitly so as to load on one factor while being orthogonal to the other.

Using our jump risk factor, we find strong evidence that aggregate stock market jump risk is priced in the cross-section. Aggregate market jump risk is important economically: a two-standard-deviation increase across stocks in jump factor loadings is associated with a 3.5% to 5.1% drop in expected annual returns (respectively with and without corrections for market, size, and BM loadings). We find that the compensation for bearing stock market volatility risk is similar albeit a bit smaller: a two-standard-deviation increase across stocks in volatility factor loadings is associated with a 2.7% to 2.9% drop in expected annual returns (again with and without corrections for market, size, and BM loadings). These results are robust to various additional risk controls and alternative proxies for volatility and jump risk.

Several important implications emerge from our analysis. First, the cross-sectional evidence is in line with the results in the related time-series literature, which suggests that time-varying aggregate jump risk has a large effect on aggregate market returns. Second, jump and volatility risk are separately priced sources of risk. Third, jump risk and volatility risk betas are nearly uncorrelated. This implies that the firm characteristics that make firms good hedges against jump risk are different from the characteristics that make firms good hedges against volatility risk. Fourth, jump and volatility risk betas are time-varying. Nevertheless, both future jump and volatility risk betas can be predicted, and thus implementable strategies to hedge against these sources of risk can be found.

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Appendix

In this appendix, we show that instantaneous excess straddle returns are proportional to innovations in volatility in the Heston (1993) stochastic volatility model. Assume that the asset price S_t at time t and its variance V_t follow the diffusions

$$dS_t = (\mu - \delta)\, S_t dt + S_t \sqrt{V_t} dZ_{1t}, \tag{A1}$$

$$dV_t = \kappa\,(\theta - V_t)\, dt + \sigma \sqrt{V_t} dZ_{2t}, \tag{A2}$$

where Z_{1t} and Z_{2t} are P-Brownian motions with correlation ρ, and δ is the dividend yield.

Heston (1993) shows that the value of any derivative $U\,(S_t, V_t, t)$ must satisfy the partial differential equation

$$\begin{aligned}\frac{1}{2} V_t S_t^2 \frac{\partial^2 U}{\partial S^2} + \rho\sigma V_t S_t \frac{\partial^2 U}{\partial S \partial V} + \frac{1}{2}\sigma^2 V_t \frac{\partial^2 U}{\partial V^2} + (r - \delta)\, S_t \frac{\partial U}{\partial S} \\ + \left[\kappa\,(\theta - V_t) - \lambda\,(S_t, V_t, t)\right] \frac{\partial U}{\partial V} + \frac{\partial U}{\partial t} = rU,\end{aligned} \tag{A3}$$

which is equation (6) in Heston (1993). Here $\lambda(S_t, V_t, t)$ is the market price of volatility risk.

By Ito's Lemma,

$$dU = \left[\frac{1}{2}V_t S_t^2 \frac{\partial^2 U}{\partial S^2} + \rho\sigma V_t S_t \frac{\partial^2 U}{\partial S \partial V} + \frac{1}{2}\sigma^2 V_t \frac{\partial^2 U}{\partial V^2} + \frac{\partial U}{\partial t}\right] dt + \frac{\partial U}{\partial V} dV_t + \frac{\partial U}{\partial S} dS_t. \tag{A4}$$

Inserting the PDE into the drift gives

$$\begin{aligned} dU &= rU dt - (r-\delta) S_t \frac{\partial U}{\partial S} dt - \left[\kappa(\theta - V_t) - \lambda(S_t, V_t, t)\right] \frac{\partial U}{\partial V} dt + \frac{\partial U}{\partial V} dV_t \\ &+ \frac{\partial U}{\partial S} dS_t = rU dt + \frac{\partial U}{\partial S}\left[dS_t - (r-\delta) S_t dt\right] \\ &+ \frac{\partial U}{\partial V}\left[dV_t - \left[\kappa(\theta - V_t) - \lambda(S_t, V_t, t)\right] dt\right]. \end{aligned} \tag{A5}$$

Therefore, instantaneous option returns satisfy

$$\begin{aligned} \frac{dU}{U} &= rdt + \frac{\partial U}{\partial S} \cdot \frac{S_t}{U}\left[\frac{dS_t}{S_t} - (r-\delta) dt\right] \\ &+ \frac{\partial U}{\partial V} \cdot \frac{1}{U}\left[dV_t - \left[\kappa(\theta - V_t) - \lambda(S_t, V_t, t)\right] dt\right]. \end{aligned} \tag{A6}$$

Let STR denote the price of a delta-neutral straddle. It follows that instantaneous straddle returns satisfy

$$\begin{aligned} \frac{dSTR}{STR} &= rdt + \frac{\partial STR}{\partial V} \cdot \frac{1}{STR} dV_t \\ &- \frac{\partial STR}{\partial V} \cdot \frac{1}{STR}\left[\kappa(\theta - V_t) - \lambda(S_t, V_t, t)\right] dt, \end{aligned} \tag{A7}$$

such that

$$\frac{dSTR}{STR} = rdt + \frac{\partial STR}{\partial V} \cdot \frac{1}{STR}\left(dV_t - E_t^Q\left[dV_t\right]\right), \tag{A8}$$

where Q is the equivalent martingale measure, which implies that (excess) straddle returns are locally proportional to innovations in volatility.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.