Aggregate Volatility and Market Jump Risk: A Risk-Based Explanation to Size and Value Premia

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Abstract

Previous studies document that volatility risk is priced in the cross-section of stock returns. Driven by evidence from option pricing literature that stock prices exhibit both stochastic volatility and jumps, I test whether market jump risk is priced differently from volatility risk. In addition to earlier findings which document a negative price for volatility risk, I find that jump risk is priced separately, and is negative. Furthermore, I document significant differences between volatility and jump risk factor loadings of value vs. growth, and small vs. big portfolios. Due to differences in their volatility and jump risk loadings, investors require an additional return of 0.86% per month on a portfolio, which longs stocks in the smallest size decile and shorts stocks in the biggest size decile. Similarly, a portfolio which longs value stocks and shorts growth stocks will on average require an additional return of 0.59% per month.

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Stocks with small market capitalizations tend to earn higher returns than stocks with larger market capitalizations, also known as the size anomaly.[1] A very much related phenomenon that has been observed in common stock returns is that value stocks earn higher average returns compared to their growth counterparts, known as the value premium.[2] Fama and French (1993, 1996) argue that the size and value premium are compensations for risks that are not captured by the capital asset pricing model (CAPM), and document that including factors such as SMB and HML helps explain a large cross-section of expected returns. According to Cochrane (2001), Fama-French mimicking portfolios indicate the existence of a distress or recession factor, which affects small and value stocks fundamentally in a different way than big and growth stocks. On the other hand, according to the investor overreaction theory of Lakonishok, Shleifer, and Vishny (1994), size and value premium in average returns arise because investors undervalue distressed stocks and overvalue big and growth stocks. When these pricing errors are corrected, value stocks have lower returns and growth stocks have higher returns.[3]

Do investors really behave sub-optimally and overreact to prices as argued by behavioral explanations, or are value and small firms fundamentally riskier than their growth and big counterparts? If we assume that investors are rational, and the former are indeed riskier, what are the economic factors that generate common variation in the earnings of these firms? In other

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[1] See Banz (1981) and Reinganum (1981) for first studies documenting the size anomaly.

[2] Firms with high ratios of book-to-market equity (B/M), earnings to price (E/P), cash flow to price (C/P), or dividend yield (D/P) are often referred to as "value" stocks, whereas firms with low B/M, E/P, C/P, or D/P ratios are referred to as "growth" stocks.

[3] La Porta (1996) and La Porta, Lakonishok, Shleifer, and Vishny (1997) also reach similar conclusions.

words, what are the specific risk factors that lead investors to demand higher returns on small and value stocks, and lower returns on big and growth stocks, than predicted by the CAPM? The purpose of this paper is to answer these questions within a rational expectations framework, and from a volatility and jump risk perspective. I argue that it is the sensitivity of stocks to innovations in aggregate volatility and market jump risk, which determines investors' associated risk-return tradeoffs. In other words, aggregate volatility and market jump risk are the economy-wide factors that drive the differences in the earnings of small vs. big, and value vs. growth stocks. If this is the case, it implies that volatility and jump risk must be priced risk factors, and should help explain the cross-section of common stock returns.

To test the above hypotheses, one has to find suitable and observable proxies that take into account investors' true measures of volatility and jump risks. To do that, I use two measures from the options market that are able to summarize investors' information set on aggregate volatility and jumps in the market. There are four main reasons in resorting to measures from the options market. First, prices formed in options market are forward looking, and contain valuable information about investors' expectations about the return process of the underlying. For example, VIX index gives information about investors' expectations on the evolution of future volatility in the market, also known as the investor sentiment.[4] Second, in the presence of real-life market frictions, options are non-redundant securities, and help investors replicate their consumption-payoff patterns, which otherwise is not possible with the existing assets in the

[4] The VIX Index is an implied volatility index that measures the market's expectation of 30-day S&P 500 volatility implicit in the prices of near-term S&P 500 options.

market.[5] For example, Liu and Pan (2003) show that when stock price dynamics are driven by stochastic volatility and jumps, holding a risky and a risk-free asset is not sufficient to replicate certain payoff patterns due to volatility and jump risks, which leads investors to hold at-the-money straddles, and out-of-money puts in their optimal portfolios. Third, when markets are incomplete, Detemple and Selden (1991) show that there should be a general interaction between options market and the stock market. In line with this theory, recent stream of studies explore this relationship by using option returns as explanatory factors in the cross-section of stock returns.[6] Finally, because options themselves are tradable assets, using straddle returns as a proxy for volatility risk helps avoid the problem of mimicking portfolios, and helps better represent a dynamically managed portfolio that corresponds to investors' true investment opportunity set.

In line with the spirit of this paper, recent studies document that volatility risk and downside risk are priced risk factors in the cross-section of stock returns. In separate studies, Ang et al. (2006), and Moise (2007) document that volatility risk is priced in the cross-section of U.S. stock returns, and is negative. Furthermore, Ang, Chen, and Xing (2006) find that stocks that covary strongly with the market when the market declines have high average returns, estimating a positive downside risk premium of approximately 6% per annum. Although similar in spirit, this paper differs from the three in several ways. First of all, as opposed to the above studies, I separate jump risk from volatility risk. There is now considerable evidence from the

[5] See Back (1993), Grossman and Zhou (1996), Easley, O'Hara, and Srinivas (1998), Basak and Croitoru (2000), Bates (2001), Lee and Yi (2001), Buraschi and Jiltsov (2003) for articles that motivate options trading under different market imperfections.

[6] See Coval and Shumway (2001), Vanden (2004), and Arisoy, Salih, and Akdeniz (2007) for articles that document the explanatory power of option returns in the cross-section of equity returns.

option pricing literature that stock prices exhibit both stochastic volatility and sudden jumps.[7] Furthermore, as reported by French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993), periods of high volatility are usually associated with jumps and downward market moves. However, studies that examine volatility risk and jump risk usually ignore this intertwined relation between the two, and assume either volatility, or jump risk component is priced. The analysis here instead builds up on the assumption that investors care not only about innovations in aggregate volatility, but also about unfavorable sudden jumps in the market. Thus, I argue that aggregate volatility and market jump risk are priced differently, and both risk factors need to be examined separately by disentangling their effects in the cross-section of returns. Second, our measures of volatility and jump risk differ from the three considerably. Ang, Chen, and Xing (2006) define downside risk as the covariation of an asset's return with that of the market when the market is declining. Moise (2007) uses innovations in realized market volatility as a proxy for systematic volatility risk, and finally Ang et al. (2006) use innovations in the VIX index to proxy for aggregate volatility risk. The latter is closer to the one presented here by using a measure from the options market.

More specifically, I use tradable assets from the index option market that have the advantage of representing investors' true opportunity set more realistically than statistical measures. In particular, I measure volatility risk by using returns on crash-neutral at-the-money (ATM) straddles of the S&P 500 index. The crash-neutral at-the-money straddle consists of a

[7] See Bakshi, Cao,and Chen (1997), Chernov and Ghysels (2000), Bates (2000), Andersen, Benzoni, and Lund (2001), Bakshi and Kapadia (2001), Benzoni (2002), and Pan (2002) that document the importance of stochastic volatility and jumps in stock returns.

long position in an at-the-money straddle, and a short position in a deep out-of-money (OTM) put option (with 0.96 strike-to-spot ratio).[8] Adding an opposite position in a deep OTM put option reduces the sensitivity of the crash-neutral ATM straddle to downward jump risk considerably, and helps orthogonalize the two risk factors, so that volatility and jump risk factors can be disentangled, and separately analyzed. For proxying jump risk, I use returns on out-of-money puts of the S&P 500 index (with 0.98 strike-to-spot ratio), where it is assumed that investors are averse to daily jumps of -2%, or more.[9] The results can be summarized as follows.

I document that small and value stocks consistently have negative and significant volatility and jump factor loadings, whereas big and growth stocks exhibit positive and significant volatility and jump loadings. Together with the fact that crash-neutral ATM straddles on average earn positive (negative) returns at times of high (low) volatility, this implies small and value stocks are expected to lose (earn) more than their big and growth counterparts at times of high (low) aggregate volatility. Similarly, OTM put options experience significant positive (negative) returns in the case of negative (positive) jumps in the market. This empirical observation together with the observed negative jump loadings for small and value stocks imply that they are expected to lose (earn) more than their big and growth counterparts at times of negative (positive) jumps in the market.

Furthermore, portfolio sensitivities with respect to aggregate volatility and market jump risk are also time-varying. Especially, the volatility beta dispersions between big and small

[8] See Coval and Shumway (2001), and Driessen and Maenhout (2006) on the construction of crash-neutral straddles.

[9] I try different magnitudes of daily jumps ranging from -2% to -4%. The findings are robust to changes in jump magnitudes.

portfolios, and growth and value portfolios change considerably (nearly halves) when going from a high volatility regime to a low volatility regime, and when going from months that exhibit significant negative jumps to months that do not. This implies that small and value stocks are much riskier at times of high volatility and negative jumps on the market compared to their big and growth counterparts.

Finally, I document that aggregate volatility risk and market jump risk are priced risk factors. Consistent with Ang et al. (2006), and Moise (2007), I document a negative price for aggregate volatility risk. More interestingly, the risk premium estimates indicate that, market jump risk is also priced in the cross-section. During the sample period studied, the cross-section of stock returns exhibit a negative and significant jump risk premium. The result confirms the hypothesis that investors indeed treat jump risk differently than volatility risk, and reflect this as a separate risk factor in their risk-return tradeoffs.

This work is closely related to recent studies that explain value and size premium within a rational expectations framework. The business cycle explanation of Lettau and Ludvigson (2001), and Petkova and Zhang (2005) argue that it is the time variation in the conditional betas of value and growth stocks in bad and good times of the economy that create the value premium. In CCAPM and CAPM settings, respectively, the authors find that value and small stocks have lower consumption (market) betas during bad times relative to big and growth stocks, while the opposite holds during good times. I argue that it is the difference in volatility and jump risk loadings of small and big, and value and growth firms that drives the observed size and value premium in the market. Investors demand shares of big and growth firms in order to hedge against deteriorations in their wealth during periods of high volatility and negative jumps in the market. Overall, the findings lend support to a rational markets asset pricing theory, and a risk-based explanation.

The rest of the paper is organized as follows. The first section sets the theoretical and empirical framework on the need of separating jump risk from volatility risk. Section II details data and the construction of tradable proxies. Section III presents estimates of volatility and jump risk loadings for size and book-to-market portfolios. Sections IV and V test i) whether there exists time variation in volatility and jump risk loadings, and ii) whether jump risk is priced separately from volatility risk, respectively. The final section offers concluding remarks.

I. Separating Jump Risk from Volatility Risk

A. Theoretical Motivation

Economic theory suggests that if investment opportunities vary over time, then investors should not only care about market risk, but also about innovations in state variables that capture this time-variation in the investment opportunity set. This implies that risk-averse investors would demand a risk premium for those assets, which offer a hedge against deteriorations in their respective investment opportunity sets. In line with this theory, Campbell (1993) and Chen (2002) argue that risk-averse investors want to hedge not only against market risk, but also against innovations in market volatility. This is because investors are reluctant to lose wealth in periods of high volatility, which represents a deterioration in investment opportunities, and which usually coincides with periods of low consumption (recessions). For pricing purposes, this implies that an asset that has positive covariance between its return and variables that correctly predict innovations in aggregate volatility should have lower expected returns. In other words, assets whose returns correlate positively with innovations in market volatility would be seen as hedges against volatility risk, and demanded by risk-averse investors, driving their prices up, implying lower average returns.

On the other hand, according to the mean-semi variance framework of Markowitz (1959), and the prospect theory of Kahneman and Tversky (1979), investors care downside losses more than upside gains. Thus, investors who are sensitive to downside losses, relative to upside gains, should require a risk premium not only for aggregate volatility risk, but also a premium for holding assets that covary strongly with the market when the market exhibit downward market moves. Moreover, as documented by French, Schwert, and Stambaugh (1987), and Glosten, Jagannathan, and Runkle (1993), periods of high volatility usually coincides with jumps and downward market moves. Furthermore, there is strong evidence from the option pricing literature that stock price dynamics exhibit both stochastic volatility and jumps.[10] This relationship between volatility and jump processes raises a natural question. Is it the volatility risk being priced in securities returns as documented by previous studies, or is there a separate jump effect which is otherwise subsumed by aggregate market volatility? If the true behavior of the stock price process is characterized by a diffusion process and sudden jumps, and if investors care

[10] By comparing alternative option pricing models that assume different stock price dynamics, Bakshi, Cao, and Chen (1997) document that models that take into account stochastic volatility and jumps in stock prices have lower pricing and hedging errors.

downside losses more than upside gains, then there is strong reason to believe that jump risk should also be priced in the cross-section of stock returns. In this case, it becomes crucial to separate jump risk from volatility risk. Otherwise, models with volatility risk or jump risk alone would not correctly reflect the true time-variation in investors' opportunity set.

Motivated by the above findings, in this paper I assume that investors are averse not only to changes in market return, and changes in aggregate market volatility, but also to the occurrence of negative jumps in the market. Thus, contrary to previous studies, I assume that jump risk is priced differently from volatility risk. The prediction of such a model is that an asset that has positive covariance between its return, and variables that correctly predict innovations in aggregate volatility and negative jumps in the market, should have lower expected returns. If aggregate market volatility and market jump risk are priced risk factors, then they should play a role in determining the time-variation in the investment opportunity set. This implies, in equilibrium, the conditional average return on any stock is given by,

$$E_t\left(r_{t+1}^i\right) = \beta_{m,t}^i \lambda_{m,t} + \beta_{v,t}^i \lambda_{v,t} + \beta_{j,t}^i \lambda_{j,t} + \sum_{k=1}^{K} \beta_{k,t}^i \lambda_{k,t} \ , \qquad (1)$$

where $\lambda_{m,t}$ is the price of risk of the market factor, $\lambda_{v,t}$ is the price of aggregate volatility risk, $\lambda_{j,t}$ is the price of market jump risk, and the $\lambda_{k,t}$ are the prices of risk of other factors.

The above model constructs the basis of the empirical tests. More precisely, I examine, i) whether volatility and jump risk are priced risk factors in the cross-section of expected returns, ii) whether different asset classes have different factor loadings with respect to volatility and jump risk, and finally iii) whether these factor loadings are time-varying.

B. Empirical Framework

To test the above hypotheses, one has to use observable market proxies. In order to summarize investors' information set on aggregate volatility, and market jumps, I resort to two measures from the options market. There are three main reasons for doing that. First, when markets are incomplete, Detemple and Selden (1991) show that there should be a general interaction between option prices and stock prices. Second, in the case of market frictions, options are non-redundant securities, and their returns can help explain securities returns. For example, proxying volatility risk with returns on zero-beta at-the-money straddles written on the S&P 100 index, Coval and Shumway (2001) document that portfolios sorted on market capitalizations have different volatility loadings, and small sized portfolios are more prone to volatility risk. Finally and more importantly, because options themselves are tradable assets, using their returns as proxies for volatility and jump risk helps avoid the problem of mimicking portfolios, and helps better represent a dynamically managed portfolio that corresponds to investors' true investment opportunity set.

More precisely, I use returns on at-the-money (ATM) straddles and returns on out-of-money (OTM) puts written on the S&P 500 index to measure an asset's sensitivity to aggregate volatility and market jump risk, respectively. Straddles are volatility trades and their returns are very sensitive to innovations in volatility, making them ideal to study the effect of innovations in aggregate volatility. On the other hand, investors demand out-of-money puts to hedge their positions against significant downward moves in the market. By paying a relatively small premium and buying an out-of-money put option, an investor can protect herself against negative and unfavorable jumps in the market. Because out-of-money put options are highly sensitive to negative jumps in the market, their returns are ideal for proxying market jump risk.

There are two main issues to be noted here. First, I assume that investors price volatility and jump risk separately. However, as reported by French, Schwert, and Stambaugh (1987), periods of high volatility usually coincides with negative stock returns. Thus, in order to test for the effects of volatility and jump risk separately, one has to control for this intertwined relation, and separate the dynamics between the two. In the framework of this paper this translates to "the price of an at-the-money straddle should not contain any information on the occurrence of negative jumps in the market". To do that, I follow Driessen and Maenhout (2006), and form a crash-neutral ATM straddle. The crash-neutral ATM straddle consists of a long position in an ATM straddle, and a short position in a deep OTM put option. Crash-neutralizing the ATM straddle makes it insensitive to significant downward moves in the market. This, in turn, helps partially orthogonalize the two risk factors, so that the pricing of volatility and jump risk factors can be isolated, and separately analyzed. Second issue is the price of market jump risk. It is not an easy task to correctly specify the exact magnitude of market jump that the investors are averse to. As there are theoretically infinite number of jump sizes ranging from 0 to -100%, one has to define a meaningful jump size. I assume that investors are averse to daily jumps of -2% in the market (-9.6% weekly), and thus, use returns on out-of-money puts with 0.98 strike-to-spot ratio in order to capture investors measure of market jump risk. The prices of OTM puts with 0.98 strike-to-spot ratio contain information about investors' expectations on jumps of magnitude -2%

or more, and by construction, their returns are very sensitive to the occurrence of jumps in the market. Thus, the covariance of an asset's return with the return on this option will yield information about the sensitivity of the asset to jumps in the market.

Finally, because the true conditional factor loadings in Equation (1) are unobservable, I do not directly use it in empirical estimations. Instead, I specify the full model as,

$$r_t^i = \alpha_0 + \beta_{MKT}^i MKT_t + \beta_{ATM}^i ATM_t + \beta_{OTM}^i OTM_t + \varepsilon_t^i . \tag{2}$$

Here, r^i_t is the excess return of test asset i, MKT is the excess market return, and ATM, and OTM are excess returns on crash-neutral at-the-money straddles, and out-of-money puts written on the S&P 500 index, which proxy for aggregate market volatility and market jump risk, respectively. β^i_{MKT}, β^i_{ATM}, and β^i_{OTM} are the estimated factor loadings of market risk, aggregate volatility risk, and market jump risk, respectively.

The following section details the construction of tradable proxies for aggregate volatility and market jump risk, presents the data, and documents the results of empirical tests of Equation (2).

II. Data and Construction of Tradable Proxies

For tests of Equation (2), and to see whether volatility and jump risk factors can potentially explain the observed size, and value vs. growth anomalies in U.S. returns, I use portfolios with stocks sorted according to their market capitalizations, and book-to-market ratios as test portfolios.[11] For market proxy, I use CRSP's value-weighted market index for all NYSE, AMEX, and NASDAQ stocks. The risk-free rate is the 1-month T-Bill rate. Daily closing prices of calls and puts on S&P 500 index (SPX) are obtained from Chicago Board Options Exchange's (CBOE) Market Data Express (MDX). Overall, the sample covers the period from January 1987 to March 2007, with a total of 243 months. Next, I detail the construction of tradable proxies for aggregate volatility risk and market jump risk.

For proxying aggregate volatility risk, I use returns on crash-neutral ATM straddles that consist of one long position in an ATM straddle and one short position in a deep OTM put. More specifically, an ATM straddle return is the equally weighted return on 1 long call and 1 long put with strike prices just above the spot price, $-5 < S\text{-}K < 0$, and 1 long call and 1 long put with strike prices just below the spot price, $0 < S\text{-}K < 5$. A deep out-of-money put has a strike-to-spot ratio of 0.96, which guarantees that the crash-neutral ATM straddle is insensitive to daily crash magnitudes of 4%, or above. For market jump risk, I use returns on out-of-money put options with a strike-to-spot ratio of 0.98.

Before computing the returns on crash-neutral ATM straddles and OTM puts, the following filtering criteria is applied. First, I eliminate all options with prices that violate arbitrage pricing bounds and put-call parity by more than 1%. Then, options that expire during the following calendar month are identified. The reason for choosing options that expire the next

[11] More precisely, I use value-weighted returns on 10 portfolios sorted according to their market capitalizations, 10 portfolios sorted according to their book-to-market ratios, 25 portfolios (5x5) sorted according to size and book-to-market ratios, and 6 portfolios (2x3) sorted according to size and book-to-market ratios, all of which are downloaded from Ken French's data library.

calendar month is that they are the most liquid data among various maturities.[12] Options that expire within 10 days are also excluded from the sample because they show large deviations in trading volumes, which casts doubt on the reliability of their pricing.[13] Next, each option is checked whether it is traded the next trading day or not. If no option is found in the nearest expiry contracts, then options in the second-nearest expiry contracts (expiring in two calendar months) are used.

After applying these criteria, I compute daily call and put returns by using raw net returns. Then, the daily return on a crash-neutral straddle is simply the difference between the equally-weighted return on two ATM straddle positions with strike prices right above and below spot price, and the return on a deep OTM out option with a 0.96 strike-to-spot ratio. For returns on OTM puts, I apply the following criteria. First, I check whether an out-of-money put option exists with a strike-to-spot ratio of 0.98. As described previously, this option strategy guarantees to protect its investor from daily jumps of magnitudes -2% or above. If no option is found in that moneyness bin that expire within next two calendar months, then I look for an out-of-money put in the moneyness bin closest to and higher than 0.98. Choosing an OTM put with a strike-to-spot ratio of less than 0.98 would always leave some portion of the jump risk be unhedged. Thus, by choosing the second best alternative, i.e. an OTM put with a strike-to-spot ratio of 0.98 or higher, the investor is always protected against jumps of magnitude of -2% or higher.

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[12] According to Buraschi and Jackwerth (2001), most of the trading activity in S&P 500 options is concentrated in the nearest (0–30 days to expiry), and second nearest (30–60 days to expiry) contracts.

[13] Stoll and Whaley (1987) report abnormal trading volumes for options close to expiry.

<< Insert Table 1 about here>>

Before proceeding with the formal tests, Table 1 presents the descriptive statistics of the data used in this study. Panels A and B summarize daily returns of calls and puts written on the S&P 500 index with respect to 8 moneyness levels. Consistent with previous studies, average daily call (put) returns during the period from January 1987 to March 2007 are positive (negative) regardless of their moneyness levels. Furthermore, daily call returns increase monotonically from the deepest in-the-money calls to deepest out-of-money calls. The deepest-out-of-money calls earned an impressive daily return of 1.97% on average throughout the sample period. A similar pattern is observed for average put returns. Although not monotonically, daily put returns seem to decrease from deepest in-the-money puts to deepest out-of-money puts, with deepest out-of-money puts losing 5.69% on average daily.

Panel C of Table 1 reports monthly average returns on ATM straddles, OTM puts, crash-neutral ATM straddles which form the basis for tests of Equation (2). It is clear that selling ATM straddles, and OTM puts earned their investors a significant return throughout the sample period. On average, selling ATM straddles earned 8.16% per month, while selling out-of-money puts with a 0.98 strike-to-spot ratio earned an impressive 36.83% per month, compared to 1.01% earned from investing in the market portfolio. The findings are in line with previous studies. For example, Coval and Shumway (2001) report weekly returns of -3.15% and -3.24% for ATM straddles and crash-neutral ATM straddles, respectively. Driessen and Maenhout (2006) document weekly returns of -1.67% and -4.78% for the returns on ATM straddles and OTM puts with 0.96 strike-to-spot ratio. Broadie, Chernov, and Johannes (2007) report monthly returns of -15.7% and -44.7% for ATM straddles and out-of-money puts with 0.98 strike-to-spot ratio. Finally, Bondarenko (2006) reports an average monthly return of -54% for OTM puts with 0.98 strike-to-spot ratio.

Finally, Panel D of Table 1 presents correlations between monthly returns on ATM straddles, OTM puts, crash-neutral ATM straddles, and the market portfolio. As can be seen, crash-neutralizing the ATM straddle significantly reduces its correlation with the OTM put. This in turn helps orthogonalize the returns between the two, which is crucial in order to examine the effects of volatility and jump risk separately.

The next section presents the results for tests of the first hypothesis of this paper, which tests whether there exist differences in the sensitivity of returns of different portfolios with respect to aggregate volatility and jump risk factors.

III. Volatility and Jump Risk Factor Loadings

This section presents volatility and jump risk loadings of different portfolios consisting of stocks sorted with respect to their market capitalizations and book-to market ratios. More specifically, I estimate Equation (2) using excess monthly returns on the CRSP value-weighted market index as a proxy for market risk, and excess monthly returns on crash-neutral ATM straddles and OTM puts as proxies for volatility and jump risk, respectively.

<< Insert Table 2 about here>>

Table 2 presents the factor loadings of 10 portfolios sorted according to their market capitalizations. As can be seen, portfolios in the smallest 9 deciles consistently have negative and significant volatility and jump loadings. On the contrary, the biggest size decile exhibits positive and significant loadings for both volatility and jump risk factors. More interestingly, volatility and jump risk loadings increase almost monotonously from the smallest size decile to the biggest. As far as the author knows, this is the first study that documents the difference in the sensitivities of portfolios with respect to aggregate volatility and market jump risk.[14] The results, if persistent, might offer an alternative explanation to the previously documented size anomaly, and can have important pricing implications.

ATM straddles are volatility trades, and their returns are positive (negative) when aggregate volatility is high (low). This relationship implies that, assets with negative volatility risk loadings, i.e. small stocks, are expected to earn lower returns at times of high volatility. On the contrary, due to their positive volatility risk loadings, stocks in the biggest size decile protect their investors against innovations in volatility A similar pattern is observed with respect to jump risk. OTM puts exhibit positive (negative) returns at times of negative (positive) jumps in the market. This implies, when market exhibit negative jumps, an asset with a negative (positive) jump risk loading will earn lower (higher) returns than predicted by the CAPM. Thus, because of their negative covariation with innovations in aggregate volatility and negative jumps in the

[14] The difference in the volatility factor loadings between small and big portfolios was a phenomenon previously reported by Coval and Shumway (2001).

market, investors will require an additional premium for holding small stocks. Furthermore, big stocks covary positively with innovations in aggregate volatility, and negative jumps in the market. Because of their positive volatility and jump betas, stocks with higher market capitalizations will earn more (or lose less) than their small counterparts, thus will be more attractive compared to stocks with lower market capitalizations at times of high aggregate volatility and negative jumps in the market. Positive volatility and jump risk loadings for the biggest size decile imply that stocks with big market capitalizations offer a hedge against volatility and jump risks, and thus will be demanded by investors who would like to protect themselves against deteriorations in their investment opportunity sets due to those risks. This implies a higher demanded for big stocks by risk-averse investors, implying higher prices, thus lower returns for them. The results support a “flight-to-quality” explanation at times of high aggregate volatility, and downward market moves.

<< Insert Table 3 about here >>

Next, I examine factor loadings of portfolios with stocks sorted according to their book-to-market ratios. Looking at Table 3, one can observe similar, but slightly weaker results. The volatility factor loadings are negative for 8 of the portfolios with high book-to-market ratios, and positive for 2 portfolios with low book-to-market ratios. The jump loadings are negative for 7 of the highest book-to-market ratio portfolios, and positive for 3 of the lowest book-to-market ratio portfolios. However, volatility and jump loadings are significant only for the three highest book-to-market portfolios (value portfolios), and positive and significant only for the lowest book-to-market portfolio (growth portfolio). Again, it seems that growth stocks tend to offer a natural hedge against volatility and jump risk in the market. To the best of my knowledge, this difference in the sensitivities of value and growth portfolios with respect to volatility and jump risk factors has not been documented before.

However, the results regarding the book-to-market portfolios should be approached with care. Because, by definition, the book-to-market ratio of a firm already contains some information on the market capitalization of that firm, thus there could potentially be a hidden size effect for value and growth portfolios, i.e. the significance of volatility and jump risk loadings might be due to the possible existence of many low (high) market capitalization firms in value (growth) portfolios. In order to overcome this, and verify that the significant results for value and growth portfolios are not due to a potential size effect, I further refine the test portfolios, and examine the factor loadings of 25 portfolios sorted with respect to 5 size, and 5 book-to-market portfolios.

<< Insert Table 4 about here >>

Looking at Table 4, one can see that volatility risk loadings are significant for 16 out of 25 portfolios, and jump risk loadings are significant for 17 out of 25 portfolios. Among value portfolios, it is only the portfolios in the smallest three quintiles (S-H, 2-H, and 3-H), which have significant and negative volatility and jump risk loadings. Furthermore, looking at the growth quintiles, one can see that it is only the portfolio in the biggest size quintile (B-L), which exhibits significant and positive volatility and jump loadings. This finding, if persistent, indicates that not all growth stocks but only growth stocks among big stocks, actually act as a hedge against innovations in aggregate volatility and market jump risk. To further examine this hypothesis, I refine the test portfolios to 6 portfolios sorted according to 2 size and 3 book-to-market portfolios. Table 5 presents the results of volatility and jump loadings for those 6 portfolios.

<< Insert Table 5 about here >>

Consistent with the above hypothesis, one can see that among the two value portfolios, it is the one small-value portfolio which exhibits negative and significant volatility and jump loading. Similarly, when one compares the two growth portfolios, it is the big-growth portfolio which provides investors a hedge against volatility and jump risks. At times of high volatility and negative jumps in the market, due to their significant and positive volatility and jump loadings, only growth stocks among big stocks provide their investors with returns higher than predicted by the CAPM. This implies a higher demand for big-growth stocks by risk-averse investors, which in turn imply higher prices, and lower returns than the CAPM predicts.

Next, I examine the hypothesis whether the documented volatility and jump factor loadings of different portfolios exhibit time-variation between different volatility and jump regimes.

IV. Is There Time-Variation in Volatility and Jump Risk Loadings?

It has been widely documented that equity returns exhibit stochastic volatility.[15] It is also documented that equity returns show continuations in the short-term, and reversals in the long-term.[16] Furthermore, periods with negative jumps are often followed by prices going down even more, or going up by an unusual amount. Also, periods when prices rise quickly may often be followed by prices going up even more, or on the other hand by crashes. These empirical observations coupled with the theoretical support from the option pricing literature that equity returns exhibit stochastic volatility and jumps, might indicate that the sensitivity of firms with respect to volatility and jump risk might also be time-varying. The volatility loading of a stock at a highly volatile market might not be the same compared to that of a calmer market. Similarly, the jump loading of a stock might be very different in bear markets compared to bull markets.

To test the above hypotheses, I construct two different volatility and jump settings. In the first setting, I divide the sample into two subsamples, with high and low volatility regimes. In the second setting, I differentiate months that contain negative jumps of -2% or more, from the rest of the sample. The next section details the construction of those subsamples, and presents the results of time-series estimations of volatility and jump loadings for each of the 4 subsamples.

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[15] See Engle and Ng (1993), Canina and Figlewski (1993), Duffee (1995), Braun, Nelson, and Sunier (1995), Andersen (1996), Bollerslev and Mikkelsen (1999), and Bekaert and Wu (2000) for a theoretical discussion and distributional aspects of stochastic volatility of equity returns.

[16] Jegadeesh and Titman (1993) find that short-term returns tend to continue, i.e. stocks with higher returns in the past twelve months tend to have higher future returns. In contrast, DeBondt and Thaler (1985) document that stocks with low long-term past returns tend to have higher future returns.

A. High vs. Low Volatility Regimes

In order to test whether volatility and jump loadings exhibit time-variation with respect to levels of aggregate volatility, I divide the sample into months with high and low volatility. To do that, I first compute monthly historical volatilities of the S&P 500 index. If volatility in a specific month is higher than the sample mean volatility of the S&P 500 index, then this month is identified as a high volatility month. Similarly, if volatility in a specific month is lower than the sample mean, then this month is identified as a low volatility month. Using this procedure, I identify 97 months of high volatility, and 146 months of low volatility. Table 6 presents the volatility and jump factor loadings for the two volatility regimes.[17]

<< Insert Table 6 about here >>

As can be seen, volatility and jump loadings for the 10 size portfolios in the high volatility regime exhibit a very similar pattern to that of the whole sample. The smallest 9 portfolios consistently exhibit negative and significant volatility and jump loadings, whereas the biggest size portfolio exhibits positive and significant volatility and jump loadings. This confirms the previous finding that when aggregate volatility is high, small (big) firms are expected to lose (earn) more than what the CAPM predicts.

[17] I present the results for size portfolios. The results for book-to-market, and other portfolios are available upon request.

While a similar pattern is observed at times of low volatility, one can see that portfolio volatility and jump loadings are less significant, and much smaller. The significance of volatility loadings disappears for all size deciles and they become much smaller in absolute value. Furthermore, jump loadings are only significant and negative for the three smallest and significant and positive for the biggest size portfolio. Another interesting observation is the volatility and jump beta dispersion between the biggest and smallest size portfolios. Especially, the change in volatility betas is striking. The volatility beta dispersion between biggest and smallest portfolios decreases from 0.0346 to 0.0125 going from volatile regime to a calm period, which supports the hypothesis that the sensitivities of size portfolios with respect to volatility risk are time-varying. Portfolios sorted with respect to book-to-market ratios also have similar results.

The documented findings are also in line with the business cycle risk framework of Petkova and Zhang (2005). The authors document that small and value firms are riskier during recessions when expected market risk premium is high. I argue that it is the sensitivity to aggregate volatility and market jump risk that drives the value and size premium. Small and value stocks consistently have negative volatility and jump betas, and big and growth firms consistently have positive volatility and jump betas. That is, when aggregate volatility is high, small and value stocks are much riskier than their big and growth counterparts. By providing higher returns than CAPM predicts at those times, big and growth firms offer a hedge against innovations in aggregate volatility and sudden jumps in the market, which might deteriorate agents' investment opportunity set. On the contrary, at times of low volatility, small and value firms tend to outperform their big and growth counterparts, and since on average low volatility regime dominates the high volatility regime, this might offer a potential explanation the observed size and value premium.

B. Jumps vs. No-Jumps

I finally examine whether firms have different sensitivities to volatility and jump risk, between months that exhibit negative jumps and months that do not. To do that, I identify months that exhibit at least one significant negative daily jump, i.e. -2% or more, as a jump regime, and the remaining months as no-jump regime. This partitioning results in 70 jump, and 173 no-jump months throughout the whole sample period. Table 7 presents the associated volatility and jump loading estimates within these two regimes.

<< Insert Table 7 about here >>

Looking at Table 7, one can see very similar results to that of high and low volatility regimes. In periods of significant negative jumps, the smallest 9 portfolios have significant and negative volatility and jump loadings, and the biggest portfolio exhibit significant and positive loadings. A similar but less significant pattern is observed for months that do not experience significant downward jumps. Furthermore, the volatility beta dispersion between biggest and smallest portfolios goes down from 0.0373 to 0.0194, from months that exhibit significant downward jumps to months that do not. Results are similar for the unreported book-to-market portfolios. Overall, there is significant evidence that volatility risk might be time-varying, and small and value firms are riskier at times of high aggregate volatility and when markets experience significant downward moves.

As Cochrane posits, Fama-French mimicking portfolios are proxies for macroeconomic risk, and the differences in the returns of small and big firms (SMB), and value and growth firms (HML) indicate that there is some sort of distress or recession factor at work. However, empirical studies thus far, have failed to find an appropriate measure for aggregate financial distress factor sthat covary strongly with small-big, and value-growth portfolios. I document that, it is the difference in the sensitivity of small-big, and value-growth stocks to volatility and jump risk (recession and distress proxies), which determines the size and value premium. The findings documented here support the concept of “rational markets theory”, and indicate a "flight to quality" during high volatility and jump periods. Investors shift their preferences away from small and value stocks, which are considered as being more risky at those times. Instead, they use big and growth stocks, whose returns co-vary positively with innovations in volatility and jumps in the market, and therefore are expected to protect their investors during times of low market returns. This leads to higher hedging demands for big and growth stocks, higher prices and lower expected returns.

V. Is Jump Risk Priced Separately from Volatility Risk?

Up to now, I have documented significant evidence that the returns on small and value portfolios covary negatively with the returns on crash-neutral ATM straddles and OTM puts, and big and growth portfolios covary positively, implying that small and value stocks are much riskier than their big and growth counterparts when aggregate volatility is high, and when the market experiences sudden negative jumps. The documented findings lend support to a rational asset pricing theory setting, confirming that it is the existence of economy-wide risk factors that drives the observed size and value premium. If volatility and jump risk (proxied by the returns on crash-neutral ATM straddles, and OTM puts, respectively) are able to explain differences in factor loadings of different firms, then there is a strong reason to think that investors should use this information while forming their expectations about future returns. That is, if volatility and jump risk are priced risk factors, the returns on crash-neutral ATM straddles, and out-of-money puts should be among factors that determine investors' true investment opportunity set, and help constructing the pricing kernel of the economy.

To test the hypotheses that whether aggregate volatility and market jump risk are priced risk factors, I follow the standard Fama and MacBeth (1973) methodology. The full model to be tested is,

$$r_t^i = \alpha^i + \beta_{MKT}^i \lambda_{MKT} + \beta_{VOL}^i \lambda_{VOL} + \beta_{JMP}^i \lambda_{JMP} + \beta_{SMB}^i \lambda_{SMB} + \beta_{HML}^i \lambda_{HML} + \varepsilon_t^i , \quad (3)$$

where λ's represent unconditional prices of risk of various factors.

More specifically, in the first pass, portfolio betas are estimated from a single multiple time-series using the full sample. In the second pass, a cross-sectional regression is run at each time period, with full-sample betas obtained from the first pass regressions. The associated estimates for the intercept term, α^i , and the risk premia, λ's, are then given by the average of those cross-sectional regression estimates. Table 8 summarizes the risk premium estimates of the model given by Equation (3), or subsets of it.

<< Insert Table 8 about here >>

I test 6 specifications of Equation (3). The first row represents the market model. Consistent with earlier findings, CAPM is not a true representation of the pricing kernel of the economy. The market risk premium is negative and insignificant, and a single factor market model poorly explains the cross-section of returns with an adjusted R^2 of 26%. The second row estimates the price of aggregate volatility risk together with the market factor. Consistent with Ang et al. (2006) and Moise (2007), I document a negative price for volatility risk. Furthermore, adding volatility risk as a risk factor increases the explanatory power of the model significantly. The third row estimates the price of jump risk. One can see that the cross-section of stock returns exhibits a negative and significant price for market jump risk. This is in line with the loss aversion theory of Kahneman and Tversky (1979) who argue that investors care more about downside losses than upside gains. Risk-averse invstors would like to pay a premium for holding stocks whose returns covary negatively with jumps in the market.

Row 4 of Table 8 tests the main hypothesis of this paper - whether jump risk is priced separately from volatility risk. The results imply that both volatility and jump risk are priced in the cross-section of stock returns. The price of volatility risk is estimated to be –12.27%, which is statistically significant at the 5% level. Furthermore, jump risk is also priced separately in the cross-section. The price of jump risk is estimated to be -32.82%, and is also statistically significant. The results are consistent with the hypothesis that the cross-section of stock returns reflects exposure to not only aggregate volatility risk, but also to market jump risk.

A negative price for volatility risk and market jump risk imply that stocks which have positive volatility and jump risk loadings are expected to have lower returns. In contrast, stocks that covary negatively with innovations in volatility, and with jumps in the market tend to have higher average returns. Agents who are averse to innovations in volatility will demand additional compensation for holding stocks that have high sensitivities to aggregate volatility in the market. In other words, a stock whose return covaries negatively with the returns on crash-neutral at-the-money straddles (with negative volatility loadings) will be deemed as riskier. Similarly, agents who are more averse to the occurrence of negative jumps in the market compared to positive jumps (i.e. who puts more weight on losses than profits) will pay an additional premium for holding stocks that have low sensitivities to negative jumps in the market. Overall, the findings imply that it is the joint interaction between a stock's sensitivity to volatility and jump risk that determines investors' risk-return tradeoffs.

To give an example, because of its negative exposure to volatility and jump risk factors, investors will require an additional return of 0.40% per month [(-0.0206) x (-12.27) + (-0.0134) x (-32.82)] for a portfolio that consists of stocks in the smallest size decile. Again, due to differences in their sensitivities to aggregate volatility and market jump risk, a portfolio which longs the smallest decile firms and shorts the biggest decile firms will be expected to earn an additional return of 0.86% per month [(-0.0206 - 0.0060) x (-12.27) + (-0.0134 - 0.0029) x (-32.82)]. Similarly, a portfolio which longs the smallest book-to-market decile, i.e. value firms, and shorts the biggest book-to-market decile, i.e. growth firms, will on average require an additional return of 0.59% per month [(-0.0132 - 0.0094) x (-12.27) + (-0.0050 - 0.0047) x (-32.82)].

Finally, Rows 5 and 6 of Table 8 summarize the risk premium estimates for the Fama-French 3-factor model, and the full specification model as given by Equation (3), respectively. One can see that SMB portfolio does not have a significant risk premium during the sample period studied, however the HML strategy yields a positive risk premium of 0.41% per month between 1987 and 2007, which is significant at 10% level. Looking at Row 6, one can see that including SMB and HML factors in the full specification does not affect the significance of volatility and jump risk premia. Overall, the results imply that the cross-section of stock returns exhibits negative volatility and jump risk premia, and confirms the hypothesis that jump risk is priced separately from aggregate volatility risk.

VI. Conclusion

In separate studies, Ang et al. (2006), and Moise (2007) document that aggregate volatility risk is priced in the cross-section of stock returns. On the other hand, it is empirically documented that high volatility periods usually coincide with negative jumps and downward market moves. Furthermore, there is strong evidence from the option pricing literature that stock prices exhibit both stochastic volatility and jumps. This intertwined relationship between volatility and jump processes raises a natural question. Is it the volatility risk that is being priced, or is it the sensitivity of stocks to market jump risk that creates variation in their returns, or a combination of both? Using crash-neutral at-the-money straddles and out-of-money puts written on the S&P 500 index as proxies for aggregate volatility risk and market jump risk, I document the following.

Throughout the 1987-2007 period, small and value portfolios exhibit significant and negative volatility and jump risk loadings. In contrast, big and growth portfolios have significant and positive loadings. Furthermore, I document significant time-variation in the sensitivities of portfolios especially with respect to aggregate volatility risk. At times of increased aggregate volatility, and when the market experiences negative jumps, volatility dispersion between big-small, and growth-value portfolios are about two to three times compared to that of relatively calmer periods. Small (big) and value (growth) portfolios continue to exhibit significant negative (positive) volatility and jump loadings at times of high volatility, and at periods with significant downward market moves. This implies small and value portfolios are riskier during high volatility periods and when market experiences negative jumps.

The findings are in line with Lettau and Ludvigson (2001), and Petkova and Zhang (2005) who document that small and value stocks are much riskier during bad times and recessions, in conditional CCAPM and CAPM settings, respectively. I take an alternative route, and argue that it is the difference in the sensitivities of stocks with respect to aggregate volatility and market jump risk that drives observed size and value premia. More particularly, I document that big and growth stocks are seen as hedges by risk-averse investors who are reluctant to lose wealth in periods of high volatility and downward market moves, i.e. periods which are usually associated with a deterioration in investment opportunities, and which usually coincides with low consumption (recessions). Thus, a “flight-to-quality” effect is in charge. Assuming that investors dislike innovations in aggregate volatility, and place a bigger weight to downward market moves than upward moves, positive and significant volatility and jump loadings for big and growth stocks imply that they will be demanded more by those risk-averse investors, increasing their prices, thus lowering their returns.

If investors are averse to both aggregate volatility and market jump risk, then these factors should be priced in the cross-section of stock returns Consistent with earlier findings, I find that volatility risk is priced and has a negative premium. I further document that market jump risk is also priced in the cross-section, and is negative. The findings are robust to the addition of Fama-French mimicking portfolios. Overall, the results support the view of a rational asset pricing theory, and offer a risk-based explanation to the observed size and value premia.

REFERENCES

Andersen, Torben G., 1996, Return volatility and trading volume: An information flow interpretation of stochastic volatility, *Journal of Finance* 51, 169–204.

Andersen, Torben G., Luca Benzoni, and Jesper Lund, 2001, Towards an empirical foundation of continuous-time equity return models, *Journal of Finance* 57, 1239-1284.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191-1239.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xioyan Zhang, 2006, The cross section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Arisoy, Yakup E., Aslihan Salih, and Levent Akdeniz, 2007, Is volatility risk priced in the securities market? Evidence from S&P 500 index options, *Journal of Futures Markets* 27, 617-642.

Back, Kerry E., 1993, Asymmetric information and options, *Review of Financial Studies* 6, 435–472.

Bakshi, Gurdip S., and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527-566.

Bakshi, G., Charles Cao, and Zhiwu Chen 1997, Empirical performance of alternative option pricing models, *Journal of Finance* 52, 2003-2049.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Basak, Suleyman, and Benjamin Croitoru, 2000, Equilibrium mispricing in a capital market with portfolio constraints, *Review of Financial Studies* 13, 715–748.

Bates, David S., 2000, Post-’87 crash fears in the S&P500 futures option market, *Journal of Econometrics* 94, 181-238.

Bates, David S., 2001, The market for crash risk, NBER Working Paper, No. 8557.

Bekaert, Geert, and Guojun Wu, 2000, Asymmetric volatility and risk in equity markets, *Review of Financial Studies* 13, 1–42.

Benzoni, Luca, 2002, Pricing options under stochastic volatility: An empirical investigation, Working paper, University of Minnesota.

Bollerslev, Tim, and Hans O. Mikkelsen, 1999, Long-term equity anticipation securities and stock market volatility dynamics, *Journal of Econometrics* 92, 75–99.

Bondarenko, Oleg, 2006, Why are put options so expensive?, Working paper, University of Illinois at Chicago.

Braun, Philip A., Daniel B. Nelson, and Alain M. Sunier, 1995, Good news, bad news, volatility and betas, *Journal of Finance* 50, 1575–1603.

Broadie, Mark, Mikhail Chernov, and Michael S. Johannes, 2007, Understanding index option returns, Working Paper, Columbia University.

Buraschi, Andrea and Jens Jackwerth, 2001, The price of a smile. Hedging and spanning in option markets, *Review of Financial Studies* 14, 495-527.

Buraschi, Andrea, and Alexei Jiltsov. 2003. "Option volume and differences in beliefs", Working Paper, London Business School.

Campbell, John Y., 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487-512.

Canina, Linda, and Stephen Figlewski, 1993, The informational content of implied volatility, *Review of Financial Studies* 6, 659–681.

Chen, Joseph S., 2002, Intertemporal CAPM and the cross-section of stock returns, Working paper, University of Southern California.

Chernov, Mikhail, and Eric Ghysels, 2000, Towards a unified approach to the joint estimation of objective and risk neutral measures for the purpose of options valuation, *Journal of Financial Economics* 56, 407-458.

Cochrane, John H., 2001. *Asset Pricing*. (Princeton University Press, Princeton, NJ.).

Coval, Joshua D., and Tyler Shumway, 2001, Expected option returns, *Journal of Finance* 56, 983-1009.

De Bondt, Werner F.M., and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

Detemple, Jerome B., and Larry Selden, 1991, A general equilibrium analysis of option and stock market interactions, *International Economic Review* 32, 279–303.

Driessen, Joost, and Pascal J. Maenhout, 2006, The world price of jump and volatility risk, Working Paper, University of Amsterdam.

Duffie, Darrell, 1996, *Dynamic Asset Pricing Theory*. (Princeton University Press, Princeton, NJ.).

Easley, David, Maureen O'Hara, and P. S. Srinivas, 1998, Option volume and stock prices: Evidence on where informed traders trade, *Journal of Finance* 53, 431–465.

Engle, Robert F., and Victor K. Ng, 1993, Measuring and testing the impact of news on volatility, *Journal of Finance* 48, 1749–1778.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

French, Kenneth R., William G. Schwert, and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 19, 3 –29.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-1801.

Grossman, Sanford J., and Zhongquan Zhou, 1996, Equilibrium analysis of portfolio insurance, *Journal of Finance* 51, 1379–1403.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-92.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263-291.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *Journal of Finance* 51, 1715–1742.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny, 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52, 859–874.

Lee, Jason, and Cheong H. Yi, 2001, Trade size and information-motivated trading in the options and stock markets, *Journal of Financial and Quantitative Analysis* 36, 485- 501.

Lettau, Martin, and Sydney C. Ludvigson, 2001, Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238-1287.

Liu, Jun, and Jun Pan, 2003, Dynamic derivative strategies, *Journal of Financial Economics* 69, 401-430.

Markowitz, Harry M., 1959, *Portfolio Selection: Efficient Diversification of Investments* (John Wiley & Sons, New York, NY.).

Moise, Claudia E., 2007, Stochastic volatility risk and the size anomaly, Working Paper, Case Western Reserve University.

Newey, Whitney K., and Kenneth D. West, 1987, A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pan, Jun, 2002, The jump-risk premia implicit in options: Evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3-50.

Petkova, Ralitsa, and Lu Zhang, 2005, Is value riskier than growth?, *Journal of Financial Economics* 78, 187 – 202.

Reinganum, Marc R., 1981, Misspecification of capital asset pricing, empirical anomalies, *Journal of Financial Economics* 9, 19-46.

Shanken, Jay, A., 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1–33.

Stoll, Hans R., and Robert E. Whaley, 1987, Program trading and expiration day effects, *Financial Analysts Journal* 43, 16–28.

Vanden, Joel M., 2004, Options trading and the CAPM, *Review of Financial Studies* 17, 207-238.

Table I
Summary Statistics

Panels A and B of Table 1 report the descriptive statistics for the daily returns of short-maturity call and put options written on the S&P 500 index with respect to 8 moneyness levels. S represents the spot level of S&P 500 index, and K is the strike price specified on the contract. Panel C and D report the monthly returns and correlations of at-the-money straddles (STR), out-of money put options with 0.98 strike-to-spot ratio (OUT), crash-neutral at-the-money straddles (CN-STR) written on the S&P 500 index, and the market portfolio (MKT). The market portfolio is CRSP's value-weighted index for all NYSE, AMEX, and NASDAQ stocks. The sample covers the period from January 1987 to March 2007 (243 months). All the return figures are in percentages.

S-K	<-15	-15 to -10	-10 to -5	-5 to 0	0 to 5	5 to 10	10 to 15	>15
Panel A: Daily Call Returns								
Mean	1.97	1.28	1.11	0.64	0.48	0.12	0.02	0.01
Median	-4.66	-1.52	-0.89	-1.02	-0.56	-0.42	-0.19	0
Maximum	382.97	370.89	253.15	227.87	144.16	125.00	92.01	132.93
Minimum	-96.73	-94.40	-89.66	-80.10	-84.07	-76.35	-66.67	-68.46
Skewness	2.50	2.43	1.40	1.14	0.75	0.51	0.33	0.42
Kurtosis	12.77	14.47	6.06	4.54	2.58	1.73	1.17	4.63
Panel B: Daily Put Returns								
Mean	-0.33	-1.15	-1.34	-1.53	-1.63	-1.76	-1.91	-1.64
Median	-1.22	-3.03	-3.13	-3.91	-3.41	-3.64	-4.35	-5.69
Maximum	162.70	418.18	435.56	464.29	477.35	490.26	550.91	568.82
Minimum	-58.39	-78.87	-81.75	-84.86	-87.17	-96.73	-98.31	-97.47
Skewness	1.03	3.43	2.11	4.21	3.47	2.48	2.88	3.31
Mean	-0.33	-1.15	-1.34	-1.53	-1.63	-1.76	-1.91	-1.64

Panel C: Daily Factor Returns				
	STR	OUT	CN-STR	MKT
Mean	-8.16	-36.83	-11.03	1.01
Median	-14.36	-64.68	-15.78	1.52
Maximum	281.80	590.73	251.98	12.85
Minimum	-54.44	-99.33	-208.53	-22.54
Skewness	3.90	3.16	1.49	-1.07
Kurtosis	29.95	17.87	20.29	6.76
Panel D: Factor Correlations				
	STR	OUT	CN-STR	MKT
STR	1.00			
OUT	0.46	1.00		
CN-STR	0.77	0.27	1.00	
MRKT	-0.31	-0.28	-0.39	1.00

Table II
10 size portfolios

This table presents the estimates of time-series regressions that test whether aggregate volatility and jump risk have different loadings across 10 portfolios sorted with respect to market capitalizations. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. Each regression is estimated with monthly data from January 1987 through March 2007 (243 months). The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
Small	-0.0042	0.8291	-0.0206	-0.0134	0.53
	(-1.35)	(13.84***)	(-2.87***)	(-3.33***)	
Decile 2	-0.0047	1.0330	-0.0184	-0.0104	0.65
	(-1.78*)	(17.89***)	(-3.08***)	(-3.19***)	
Decile 3	-0.0036	1.0223	-0.0162	-0.0094	0.73
	(-1.77*)	(21.02***)	(-3.38***)	(-4.05***)	
Decile 4	-0.0042	1.0332	-0.0159	-0.0069	0.76
	(-2.21**)	(21.90***)	(-3.51***)	(-3.30***)	
Decile 5	-0.0023	1.0666	-0.0093	-0.0061	0.80
	(-1.46)	(26.52***)	(-2.28**)	(-3.67***)	
Decile 6	-0.0018	1.0177	-0.0074	-0.0041	0.85
	(-1.32)	(31.01***)	(-2.36**)	(-2.75***)	
Decile 7	0.0001	1.0047	-0.0083	-0.0030	0.89
	(0.13)	(36.64***)	(-3.02***)	(-3.19***)	
Decile 8	-0.0008	1.0428	-0.0047	-0.0038	0.91
	(-0.77)	(41.97***)	(-1.91*)	(-3.14**)	
Decile 9	0.0008	0.9700	-0.0038	-0.0011	0.94
	(1.04)	(45.14***)	(-2.08**)	(-1.21)	
Big	0.0016	0.9948	0.0060	0.0029	0.94
	(2.22**)	(59.61***)	(3.12***)	(3.70***)	
GRS(10,230) = 1.1969 (0.29)					

Table III
10 book-to-market portfolios

This table presents the estimates of time-series regressions that test whether aggregate volatility and jump risk have different loadings across 10 portfolios sorted with respect to book-to-market ratios. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. Each regression is estimated with monthly data from January 1987 through March 2007 (243 months). The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
High	0.0012	0.7983	-0.0132	-0.0050	0.62
	(0.51)	(12.97***)	(-2.49**)	(-1.97**)	
Decile 2	0.0021	0.7958	-0.0077	-0.0005	0.71
	(1.15)	(15.56***)	(-1.85*)	(-0.21)	
Decile 3	0.0009	0.6920	-0.0084	-0.0033	0.69
	(0.53)	(14.09***)	(-2.14**)	(-1.78*)	
Decile 4	0.0028	0.7495	-0.0052	-0.0016	0.69
	(1.54)	(15.91***)	(-1.23)	(-0.66)	
Decile 5	0.0010	0.8553	-0.0037	-0.0037	0.81
	(0.75)	(19.78***)	(-1.02)	(-0.79)	
Decile 6	0.0006	0.8222	-0.0109	-0.0016	0.76
	(0.42)	(19.65***)	(-2.63***)	(-1.04)	
Decile 7	0.0009	0.9006	-0.0060	-0.0007	0.79
	(0.63)	(18.54***)	(-1.64)	(-0.38)	
Decile 8	0.0011	0.9960	-0.0043	0.0011	0.87
	(0.88)	(32.33***)	(-1.29)	(0.68)	
Decile 9	0.0008	1.0321	0.0003	0.0026	0.90
	(0.77)	(33.50***)	(0.09)	(2.04**)	
Low	0.0015	1.1532	0.0094	0.0047	0.88
	(1.30)	(40.47***)	(2.93***)	(3.85***)	
GRS(10,230) = 1.1079 (0.36)					

Table IV
25 (5x5) portfolios sorted with respect to size and book-to-market

This table presents the estimates of time-series regressions that test whether aggregate volatility and jump risk have different loadings across 25 (5x5) portfolios sorted with respect to market capitalizations and book-to-market ratios. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. Each regression is estimated with monthly data from January 1987 through March 2007 (243 months). The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

Size	B/M	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
S	L	-0.0149	1.3151	-0.0104	-0.0160	0.57
		(-4.05***)	(17.23***)	(-1.33)	(-3.52***)	
S	2	-0.0046	1.0463	-0.0174	-0.0133	0.55
		(-1.51)	(15.38***)	(-2.58**)	(-3.74***)	
S	3	-0.0010	0.8368	-0.0218	-0.0080	0.60
		(-0.38)	(14.95***)	(-3.38***)	(-1.87*)	
S	4	0.0013	0.7554	-0.0237	-0.0080	0.59
		(0.54)	(13.31***)	(-3.31***)	(-2.56**)	
S	H	0.0001	0.7570	-0.0246	-0.0121	0.58
		(0.06)	(13.33***)	(-3.61***)	(-4.29***)	
2	L	-0.0082	1.3678	-0.0059	-0.0085	0.70
		(-3.14***)	(22.39***)	(-0.99)	(-2.93***)	
2	2	-0.0039	1.0104	-0.0188	-0.0062	0.71
		(-1.83*)	(18.22***)	(-3.18***)	(-2.68***)	
2	3	-0.0001	0.8180	-0.0201	-0.0070	0.71
		(-0.12)	(16.57***)	(-3.72***)	(-3.18***)	
2	4	-0.0005	0.7670	-0.0215	-0.0079	0.67
		(-0.23)	(14.71***)	(-3.74***)	(-3.46***)	
2	H	-0.0023	0.8244	-0.0283	-0.0096	0.67
		(0.96)	(12.83***)	(-4.80***)	(-3.54***)	
3	L	-0.0047	1.3306	0.0003	-0.0037	0.72
		(-1.92*)	(23.62***)	(0.06)	(-1.39)	
3	2	-0.0013	1.0136	-0.0128	-0.0039	0.80
		(-0.75)	(23.53***)	(-2.86***)	(-1.67*)	
3	3	-0.0002	0.8275	-0.0104	-0.0048	0.73
		(-0.13)	(16.31***)	(-2.14**)	(-2.46**)	
3	4	0.0006	0.7561	-0.0142	-0.0046	0.65
		(0.29)	(14.14***)	(-2.96***)	(-1.87*)	
3	H	0.0010	0.7896	-0.0173	-0.0076	0.66
		(0.43)	(12.35***)	(-2.66***)	(-2.42**)	
4	L	-0.0014	1.2600	0.0015	-0.0033	0.80
		(-0.83)	(29.09***)	(0.31)	(-1.82*)	
4	2	0.0001	0.9562	-0.0127	-0.0011	0.82
		(0.09)	(20.24***)	(-2.70***)	(-0.59)	
4	3	0.0011	0.8933	-0.0092	-0.0016	0.73
		(0.63)	(16.85***)	(-2.05**)	(-0.80)	
4	4	0.0019	0.7758	-0.0073	-0.0051	0.70
		(1.04)	(15.56***)	(-1.82*)	(-2.32**)	
4	H	0.0020	0.7932	-0.0097	-0.0037	0.62
		(0.87)	(11.98***)	(-1.56)	(-1.28)	

Table IV - *Continued*

Size	B/M	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
B	L	0.0026	1.0871	0.0086	0.0052	0.89
		(2.36**)	(45.94***)	(2.86***)	(4.41***)	
B	2	0.0018	0.9434	-0.0014	0.0013	0.82
		(1.38)	(24.69***)	(-0.43)	(0.79)	
B	3	0.0010	0.8291	-0.0051	-0.0004	0.74
		(0.67)	(20.31***)	(-1.37)	(-0.23)	
B	4	0.0025	0.7030	-0.0023	0.0007	0.56
		(1.31)	(13.30***)	(-0.55)	(0.29)	
B	H	0.0025	0.7910	-0.0066	0.0025	0.52
		(0.97)	(12.29***)	(-1.29)	(0.76)	
GRS(25,215) = 1.3425 (0.14)						

Table V
6 (2x3) portfolios sorted with respect to size and book-to-market

This table presents the estimates of time-series regressions that test whether aggregate volatility and jump risk have different loadings across 6 (2x3) portfolios sorted with respect to market capitalizations and book-to-market ratios. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. Each regression is estimated with monthly data from January 1987 through March 2007 (243 months). The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

Size	B/M	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
S	L	-0.0083	1.2802	-0.0073	-0.0071	0.71
		(-3.44***)	(22.91***)	(-1.31)	(-3.59***)	
S	M	-0.0005	0.8533	-0.0187	-0.0090	0.73
		(-0.30)	(17.31***)	(-3.64***)	(-3.45***)	
S	H	-0.0001	0.7786	-0.0230	-0.0095	0.70
		(-0.06)	(14.13***)	(-3.91***)	(-3.92***)	
B	L	0.0017	1.0911	0.0053	0.0039	0.95
		(2.16**)	(67.36***)	(2.71***)	(4.48***)	
B	M	0.0013	0.8318	-0.0046	-0.0006	0.79
		(1.01)	(20.11***)	(-1.29)	(-0.45)	
B	H	0.0017	0.7523	-0.0069	-0.0005	0.66
		(0.92)	(14.48***)	(-1.63)	(-0.24)	
GRS(6,234) = 0.6917 (0.66)						

Table VI
Volatility and Jump Beta Estimates in High and Low Volatility Regimes

This table presents the results of time-series regressions that test whether volatility risk and jump risk are time-varying risk factors. To do that, the sample period is divided into two subsamples. High volatility regime represents months where the volatility is above the estimated average standard deviation of monthly returns of the S&P 500 index, corresponding to 97 months. Low volatility regime represents months where the volatility is below the estimated average standard deviation of monthly returns of the S&P 500 index, corresponding to 146 months. The dependent variable is the excess return on one of CRSP's size deciles. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2		α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
	High Volatility Regime (97 months)						Low Volatility Regime (146 months)				
Small	-0.0008	0.8295	-0.0261	-0.0143	0.56	Small	-0.0045	0.8205	-0.0104	-0.0122	0.42
	(-0.13)	(8.84***)	(-2.50**)	(-2.23**)			(-1.35)	(11.38***)	(-1.98**)	(-3.72***)	
Decile2	-0.0008	1.0333	-0.0247	-0.0113	0.67	Decile2	-0.0053	1.0252	-0.0069	-0.0093	0.57
	(-0.15)	(11.39***)	(-2.88***)	(-2.24**)			(-1.69*)	(13.28***)	(-0.93)	(-2.97***)	
Decile3	-0.0031	1.0304	-0.0185	-0.0109	0.77	Decile3	-0.0002	0.9761	-0.0073	-0.0051	0.60
	(-0.81)	(13.85***)	(-2.75***)	(-3.02***)			(-0.05)	(14.88***)	(-1.09)	(-1.76*)	
Decile4	-0.0035	1.0175	-0.0225	-0.0078	0.79	Decile4	-0.0013	1.0188	-0.0038	-0.0040	0.65
	(-0.98)	(14.54***)	(-3.67***)	(-2.61**)			(-0.45)	(16.30***)	(-0.58)	(-1.39)	
Decile5	-0.0012	1.0766	-0.0133	-0.0067	0.83	Decile5	-0.0001	1.0227	-0.0002	-0.0039	0.72
	(-0.38)	(18.07***)	(-2.44**)	(-2.96***)			(-0.05)	(19.77***)	(-0.03)	(-1.60)	
Decile6	-0.0018	1.0058	-0.0109	-0.0046	0.87	Decile6	0.0001	1.0123	-0.0006	-0.0023	0.79
	(-0.75)	(21.43***)	(-2.64***)	(-2.31**)			(0.02)	(23.94***)	(-0.13)	(-0.96)	
Decile7	0.0006	0.9786	-0.0127	-0.0036	0.89	Decile7	0.0007	1.0317	-0.0020	-0.0017	0.86
	(0.31)	(25.89***)	(-3.43***)	(-2.42**)			(0.46)	(28.02***)	(-0.51)	(-1.34)	
Decile8	0.0001	1.0203	-0.0065	-0.0054	0.90	Decile8	-0.0003	1.0754	-0.0018	-0.0011	0.91
	(0.04)	(27.49***)	(-1.73*)	(-3.39***)			(-0.23)	(34.14***)	(-0.52)	(-0.90)	
Decile9	0.0001	0.9212	-0.0085	-0.0018	0.94	Decile9	0.0019	1.0272	0.0020	0.0007	0.93
	(0.02)	(32.27***)	(-3.06***)	(-1.76*)			(1.34)	(36.22***)	(0.92)	(0.52)	
Big	0.0017	1.0049	0.0085	0.0029	0.95	Big	0.0008	0.9892	0.0021	0.0023	0.92
	(1.24)	(41.04***)	(3.20***)	(2.49***)			(0.74)	(40.76***)	(1.75*)	(2.11**)	
	GRS(10,84) = 1.2737 (0.26)						GRS(10,136) = 1.1821 (0.31)				

Table VII
Volatility and Jump Beta Estimates With and Without Significant Negative Jumps

This table presents the results of time-series regressions that test whether volatility risk and jump risk are time-varying risk factors. To do that, the sample period is divided into two subsamples. Jump regime represents months where the S&P 500 index has experienced at least one negative jump of magnitude -2%, or higher, corresponding to 70 months. No-jump regime represents months where the S&P 500 index did not experience any significant jumps, corresponding to 173 months. The dependent variable is the excess return on one of CRSP's size deciles. r_{MKT} is the return on CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks, r_{ATM} , is the return on crash-neutral at-the-money straddles, and r_{OTM} , is the return on out-of-money put options written on the S&P 500 index. r_{ft} is the 1-month T-bill rate. The numbers presented at the top are the coefficient estimates of time series regressions, and the numbers in the parantheses are their associated t-statistics. All t-values are corrected for autocorrelation (with lag = 3), and heteroskedasticity as suggested by Newey and West (1987). GRS F-statistic, and its associated p-value (in paranthesis) reported at the bottom of the table is from Gibbons, Ross, and Shanken (1989). *, **, *** denote significance levels at 10%, 5%, and 1%, respectively.

	α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2		α_i	β_{MKT}	β_{ATM}	β_{OTM}	Adj. R^2
	Months with Daily Jumps < - 2% (70 months)						Months with Daily Jumps > - 2% (173 months)				
Small	-0.0023	0.8089	-0.0277	-0.0138	0.53	Small	-0.0040	0.8464	-0.0162	-0.0125	0.43
	(-0.31)	(7.14***)	(-2.09**)	(-2.01**)			(-1.15)	(12.34***)	(-2.62***)	(-3.13***)	
Decile2	-0.0037	0.9848	-0.0260	-0.0105	0.65	Decile2	-0.0054	1.0794	-0.0144	-0.0105	0.57
	(-0.55)	(9.08***)	(-2.50**)	(-2.03**)			(-1.63)	(14.17***)	(-2.14**)	(-2.67***)	
Decile3	-0.0042	0.9886	-0.0220	-0.0099	0.75	Decile3	-0.0014	1.0373	-0.0089	-0.0072	0.63
	(-0.83)	(11.42***)	(-2.68***)	(-2.65**)			(-0.50)	(16.20***)	(-1.73*)	(-2.42**)	
Decile4	-0.0041	0.9869	-0.0238	-0.0070	0.77	Decile4	-0.0029	1.0678	-0.0084	-0.0062	0.68
	(-0.84)	(11.92***)	(-3.04***)	(-2.27**)			(-1.07)	(17.02***)	(-1.47)	(-2.09**)	
Decile5	-0.0010	1.0558	-0.0141	-0.0060	0.80	Decile5	-0.0022	1.0770	-0.0046	-0.0061	0.76
	(-0.22)	(14.74***)	(-2.08**)	(-2.51**)			(-0.94)	(20.77***)	(-0.91)	(-2.34**)	
Decile6	-0.0010	1.0016	-0.0109	-0.0051	0.86	Decile6	-0.0005	1.0291	-0.0029	-0.0021	0.80
	(-0.31)	(17.49***)	(-2.16**)	(-2.35**)			(-0.24)	(26.38***)	(-0.80)	(-0.94)	
Decile7	0.0019	0.9856	-0.0131	-0.0037	0.89	Decile7	-0.0001	1.0269	-0.0057	-0.0020	0.85
	(0.70)	(23.93***)	(-2.79***)	(-2.35***)			(-0.03)	(24.81***)	(-1.53)	(-1.56)	
Decile8	0.0013	1.0231	-0.0082	-0.0057	0.91	Decile8	-0.0001	1.0666	-0.0020	-0.0011	0.90
	(0.49)	(23.48***)	(-2.06**)	(-3.46***)			(-0.13)	(32.76***)	(-0.75)	(-0.90)	
Decile9	0.0008	0.9511	-0.0066	-0.0020	0.95	Decile9	0.0024	0.9793	0.0001	0.0010	0.91
	(0.44)	(38.97***)	(-2.08**)	(-2.05**)			(1.80*)	(25.44***)	(0.04)	(0.68)	
Big	0.0014	1.0141	0.0096	0.0028	0.94	Big	0.0013	0.9790	0.0032	0.0027	0.92
	(0.77)	(33.28***)	(3.08***)	(2.22**)			(1.34)	(47.94***)	(1.62)	(2.49**)	
	GRS(10,57) = 0.9461 (0.50)						GRS(10,160) = 0.7627 (0.66)				

Table VIII
Fama-MacBeth Risk Premium Estimates

This table reports the estimates for the cross-sectional Fama-MacBeth (1973) regressions specified by Equation (3), or subsets of it, using the excess returns on 25 (5x5) portfolios sorted with respect to market capitalizations and book-to-marker ratios, as test portfolios. The sample period is from January 1987 to March 2007 (243 months). The numbers in parentheses are the two t-statistics for each coefficient estimate. The top statistic uses Fama-MacBeth standard errors. the bottom statistic uses Shanken (1992) correction. The term adjusted R^2 denotes the cross-sectional R^2 statistic adjusted for the degrees of freedom.

	α_i	λ_{MKT}	λ_{VOL}	λ_{JMP}	λ_{SMB}	λ_{HML}	Adj. R^2
Row1	1.63	-0.81					0.26
	(3.11***)	(-1.33)					
	(3.08***)	(-1.32)					
Row2	1.43	-0.76	-13.35				0.44
	(2.40**)	(-1.19)	(-2.47**)				
	(2.31**)	(-1.15)	(-2.38**)				
Row3	1.68	-0.97		-36.61			0.40
	(3.33***)	(-1.56)		(-2.15**)			
	(3.21***)	(-1.49)		(-2.08**)			
Row4	1.29	-0.62	-12.27	-32.82			0.53
	(2.50**)	(-1.09)	(-2.13**)	(-1.97**)			
	(2.42**)	(-1.07)	(-2.06**)	(-1.91*)			
Row5	1.96	-1.25			0.04	0.41	0.51
	(5.47***)	(-2.75***)			(0.19)	(1.94*)	
	(5.25***)	(-2.70***)			(0.18)	(1.86*)	
Row6	1.76	-1.06	-15.83	-31.97	0.04	0.39	0.62
	(4.77***)	(-2.30**)	(-2.28**)	(-2.00**)	(0.17)	(1.87*)	
	(4.42***)	(-2.14**)	(-2.16**)	(-1.89*)	(0.16)	(1.74*)	