Macroeconomic uncertainty and option returns

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Abstract

I empirically study whether macroeconomic uncertainty is a priced risk factor in the cross-section of option returns. The analysis employs a factor model, estimated with the Fama-MacBeth methodology, in order to impose little structure on the data. The macroeconomic uncertainty factor is based on options' "excess" pricing errors on days immediately before scheduled macroeconomic announcements. The results suggest that macroeconomic uncertainty contributes to the cross-section of expected option returns, even after controlling for a large set of relevant factors. The conclusions are also robust to measurement error in stock and option prices, and to possible biases generated by the non-linearity of option returns.

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1 Introduction

One of the best known empirical regularities of the Black-Scholes option pricing model is the *volatility smile*, which is the expensiveness of out-of-the-money options relative to at-the-money ones.[1] A large part of the recent option pricing literature has tried to explain this and other stylised facts, like the change in the shape of the volatility smile after the October 1987 crash, by relaxing the Black-Scholes assumptions and incorporating additional sources of uncertainty, notably stochastic volatility and jumps.[2]

The most common approach to building an option pricing model involves specifying the distribution of the underlying asset's returns and identifying the sources of uncertainty that carry a risk premium. Priced sources of uncertainty have different parameters in the objective and risk-neutral distributions. If the volatility of jumps is priced, for instance, the risk-neutral jump volatility will not be equal to the objective one. This is the reason why differences between the estimated objective and risk-neutral parameters are usually interpreted as risk premia.

During estimation, risk premia effectively act as free parameters that reconcile any discrepancies between the objective and risk-neutral distributions. One important consequence is that model misspecification can appear as a risk premium, and specification tests are of primary importance (see Broadie, Chernov and Johannes (2007a)).

Econometric issues aside, a reduced-form approach to option pricing also poses questions in terms of economic interpretation. Investors' preferences are not explicitly defined,

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1 The Black-Scholes implied volatility is the volatility that makes the Black-Scholes price equal to the market price of an option, for given stock price, interest rate, dividends, maturity and strike price. The implied volatility curve is a plot of implied volatilities across different moneyness levels, for options with the same maturity. The Black-Scholes model implies a flat curve, but observed implied volatilities for out-of-the money options are higher, hence the name volatility *smile* or *smirk*.

2 See Bakshi, Cao and Chen (1997), Bates (2003) and Benzoni, Collin-Dufresne and Goldstein (2005).

but are implied by the pricing kernel that reconciles the objective and risk-neutral distributions. The economic mechanisms that drive the sources of uncertainty are also not fully specified. The volatility of expected returns, for instance, can be generated by the interaction between the asset's return volatility and uncertainty about the value of a state variable (David and Veronesi (2002)). Option prices may also depend on the microstructure of option markets (Jameson and Wilhelm (1992), Bates (2003), Gârleanu, Pedersen and Poteshman (2007)) and on market segmentation (Pan and Poteshman (2006)). Bates (2003, p.399) clearly emphasizes the need for a sharper focus on the economic fundamentals behind the differences between the objective and risk-neutral distributions:

> To blithely attribute divergences between objective and risk-neutral probability measures to the free "risk premium" parameters within an affine model is to abdicate one's responsibilities as a financial economist.

This paper examines the contribution of macroeconomic uncertainty to option returns. In particular, I study the effect that time-varying uncertainty about the *current* value of macroeconomic variables has on option returns.[3] The focus is not on the *time-series* relation, that is if an increase in macroeconomic uncertainty translates into higher option prices and positive returns. Instead, I investigate whether the sensitivity of option returns to macroeconomic uncertainty explains the *cross-section* of option returns, which would imply that macroeconomic uncertainty is a priced risk factor.

Let us consider two examples to clarify the meaning of "macroeconomic uncertainty". The release of the official figures for August 1999's employment situation in the U.S. was scheduled on September 3, 1999. Referring to the pre-announcement day, the

[3] Defined as holding returns: $r_{t-1,t} = \frac{opt.price_t - opt.price_{t-1}}{opt.price_{t-1}}$

Financial Times wrote:[4] *"Interest rate worries returned to ambush global equity markets, as investors nervously anticipated today's US employment numbers [...]. Recent economic data have reawakened fears that the US Federal Reserve will have to move to raise interest rates again shortly"*. The following day, the same newspaper reported: *"The smaller-than-expected increase in US job creation last month [...] and the lower-than-expected increase in hourly earnings [...] was seen as reducing the likelihood of a rise in US rates [...]"*.[5]

More recently, in September 2008, the Financial Times linked heavy stock market losses to the fact that *"[...] labour market data heightened concerns that today's crucial non-farm payrolls report might be weaker than expected [...]"*.[6]

Clearly, in both cases investors were uncertain about the current state of the employment situation, and its implications for future growth prospects. Even if in one case the economy was in a phase of robust expansion, and in the other it was on the brink of a recession, uncertainty about macroeconomic fundamentals had an equally significant impact on stock prices, because news about the employment rate were going to affect policy-makers' decisions, in the first case, and assuage or reinforce expectations of a substantial economic slowdown, in the second.

Returning to the empirical analysis presented in this paper, I proxy for unobservable macroeconomic uncertainty with a factor that sorts options on the basis of their Black-Scholes *pricing errors*, measured on days immediately before scheduled *macroeconomic announcements*, and normalized with respect to pricing errors on non pre-announcement days (see Section 3.3). I find that this factor explains the cross-section of option returns,

[4] "Rate fears cast shadow ahead of jobs data", September 3, 1999.
[5] "Shares jump on bid news and US jobs report", September 4, 1999.
[6] "Worries over financial sector weigh on equities", September, 5, 2008.

and results are robust to a large set of additional relevant factors, alternative definitions of option returns, and controls for measurement error and for possible biases arising from the non-linearity of option returns.

The macroeconomic uncertainty factor is built in three steps. First, I identify days when macroeconomic uncertainty is higher. Second, I find options that have *unusual* pricing errors on such days - they likely are more sensitive to macroeconomic uncertainty. Finally, I form a factor mimicking portfolio that buys and sells options depending on whether they have a high or a low sensitivity to macroeconomic uncertainty.

The first two steps deserve further discussion. Macroeconomic uncertainty is likely higher on the day before a scheduled macroeconomic announcement. Several authors have shown that asset prices react quickly to the release of economic news (see Section 2.2), which is consistent with a rapid resolution of uncertainty. Beber and Brandt (2007), for instance, show that the implied volatility of options on macroeconomic variables,[7] which is likely very correlated with macroeconomic uncertainty, explains the reduction of stock implied volatilities after scheduled releases of economic news. More precisely, the higher the implied volatility of options on macroeconomic variables, the more substantial the drop in equity options' implied volatilities.

As for the second step, the proxy for macroeconomic uncertainty is based on pricing errors, instead of option prices, to focus on the price component that is not explained by fundamental variables like the underlying stock price, interest rates and time to maturity. The choice of using Black-Scholes pricing errors, rather than those from a more flexible model, is to make sure that the effect of macroeconomic uncertainty is not unduly captured by one of the additional moments and risk premia. To avoid, however, that

[7] Economic Derivatives, that were marketed between 2002 and 2007.

the macroeconomic uncertainty factor proxies for other variables, the empirical analysis includes a large number of relevant factors, like stochastic volatility, jumps and higher moments.

In a recent paper, Anderson, Ghysels and Juergens (2007) find that aggregate uncertainty, proxied by the dispersion of forecasts from the Survey of Professional Forecasters, helps to explain market returns and the cross-section of expected *stock* returns. While the theoretical framework is similar, there is one important difference between their work and mine. I look for the effect of macroeconomic uncertainty on option returns *beyond* the effect it has on stocks, because this provides useful information about *why* options are non-redundant securities. If investors were able to attain payoffs across states of high/low macroeconomic uncertainty by *either* buying options *or* replicating options with stocks, then the effect of macroeconomic uncertainty on options would be routed *only* through the underlying stock, and macroeconomic uncertainty would not explain the cross-section of option returns after controlling for the exposure of the underlying stocks.

Before discussing the empirical implementation and the results in detail, I review the relevant literature in Section 2. Section 3 presents the empirical methodology, describes the data and discusses test assets and factors. Section 4 analyses the results, Section 5 focuses on the robustness checks and Section 6 concludes.

2 Related literature

2.1 Uncertainty about state variables and asset pricing

Uncertainty about the *current* value of a state variable has important implications for asset pricing. Many researchers have focused on an unobservable dividend drift, and have studied its effects on stock and option prices. For example, Buraschi and Jiltsov (2006) build an option pricing model where uncertainty and heterogeneous beliefs affect option trading volume and generate an asymmetric volatility smile. They also test several implications of their model with a Difference in Beliefs index, which is based on survey data, and find that it helps to explain the volatility smile, future realized volatility, and violations of the Black-Scholes bounds on option deltas ($\Delta \in [0, 1]$ for calls and $\Delta \in [-1, 0]$).

In David and Veronesi (2002), investors try to learn the current value of the dividend drift, which follows a two-state regime-switching model with time-varying uncertainty about the true value, and the learning process itself generates stochastic volatility and stochastic correlation between returns and volatility. As a result, David and Veronesi (2002) can generate asymmetric smiles, whose slope is sometimes positive. Guidolin and Timmermann (2003) focus on a model where dividend news evolve according to a binomial lattice with unobservable probabilities. Investors use Bayes' rule to update their estimates, and the resulting dynamics generate skewed volatility smiles and a non-constant term structure of implied volatilities.

Veronesi (2000) studies a Lucas economy where investors don't observe the output growth rate, but receive a noisy signal. He finds that the risk premium can be *lower* for higher uncertainty levels. The reason is that dividend realizations affect both expectations and the hedging demand for stocks, especially if the signal is very noisy. The correlation between consumption and returns is smaller for a less precise signal, in which case the risk premium is lower. Veronesi (2000) also finds that the correlation between expected returns and volatility depends on the level of uncertainty, which suggests a reason why the empirical evidence on the time-series relation between the conditional mean and volatility of stock returns is mixed (e.g., Whitelaw (1994)).

Dubinsky and Johannes (2005) focus on the uncertainty generated by earnings announcements, which provide important information about the future profitability of a firm. They build an option pricing model that accounts for jumps on announcement dates, and find evidence of a risk premium on the uncertainty generated by earnings announcements.

Additional studies on asset pricing with incomplete information include Detemple (1986), Dothan and Feldman (1986), Brennan (1998), Pastor and Veronesi (2006).

2.2 Economic news and asset prices

The contribution of my work is to examine the relation between macroeconomic uncertainty and the cross-section of option returns, and it is clearly linked to the literature on the effect that news about economic fundamentals have on asset prices. McQueen and Roley (1993) focus on stock prices, for which the effect of macroeconomic news varies across the business-cycle, with "good" news increasing prices only when the economy is weak. Balduzzi, Elton and Green (2001) examine the interdealer market for Treasury bills and bonds, finding evidence of strong and rapid price effects. Andersen, Bollerslev, Diebold and Vega (2003)) study the foreign exchange market, showing that announcement surprises generate conditional mean jumps.

The work of Ederington and Lee (1996) and Beber and Brandt (2006,2007) is especially relevant for my analysis, because they focus on the relation between macroeconomic news and *option prices*. Ederington and Lee (1996) examine the markets for Treasury bonds, Eurodollar and Dollar/Deutschemark options. The effect of macroeconomic news depends on whether the release is scheduled or not. In the first case implied volatilities drop, but rise for unscheduled releases. Beber and Brandt (2006) also study bond options, finding that implied volatilities always decrease after announcements, irrespective of whether the content is unexpectedly positive or negative for the economy. The behavior of higher moments, however, depends on the unexpected information brought by the announcement. Beber and Brandt (2007) derive a measure of macroeconomic uncertainty by computing the implied volatility of options on macroeconomic variables. They directly test whether the drop in implied volatilities after scheduled releases is related to macroeconomic uncertainty, and their results show that higher uncertainty leads to sharper declines.

2.3 Microstructure and demand effects in option pricing

This paper is also related to the option pricing literature on market frictions and investors' demand, because I need to make sure that macroeconomic uncertainty is not proxying for known microstructure and demand pressure effects. The fact that option market-makers absorb investors' demand, and that some options are more difficult to hedge, like those with high gamma or vega,[8] has an effect on prices and spreads: Figlewski and Webb (1993) find that high short interest on the underlying stock increases the implied volatility of

[8] Gamma is the second derivative of the option price with respect to the underlying price. Vega is the first derivative of the option price with respect to volatility.

put, but not call, options, which is consistent a demand effect. Gârleanu, Pedersen and Poteshman (2007) and Bollen and Whaley (2004) show that net demand helps to explain excess implied volatility. Jameson and Wilhelm (1992) report that option spreads are increasing in gamma.

2.4 Model uncertainty

The results of this paper can also be given a broader interpretation. If macroeconomic variables are viewed as *state variables* of an economic model, then the effect of macroeconomic uncertainty can be linked to the literature on model uncertainty.

A common assumption in asset pricing is that investors base their decisions on unequivocal probabilities of future states of the world. If, however, the probability of some states can not be pinned down exactly, investors risk making their decisions on the basis of a misspecified model. When investors adapt their decision rules to account for *Knightian* uncertainty, the price of risk is generally higher and precautionary savings increase (Hansen, Sargent and Tallarini (1999), Cagetti, Hansen, Sargent and Williams (2002)). In Epstein and Wang (1994), Knightian uncertainty can also generate excess volatility if it is high enough that prices become sensitive to non-fundamental information (more precisely, there may exist equilibria with undetermined prices).

Model uncertainty has implications for the cross-section of option prices, too. Liu, Pan and Wang (2005) focus on uncertainty aversion toward rare events, for which model specification and estimation are intrinsically difficult. They are able to reproduce the volatility smirk because options, and especially out-of-the-money puts, are very sensitive to rare events. Buraschi and Jiltsov (2006) study uncertainty about the dividend drift in a heterogeneous beliefs setting, and in their case the volatility smirk arises because of trading generated by differences in beliefs.

The literature on portfolio choice has also examined the implications of model uncertainty. Pastor and Stambaugh (2000) compare asset allocations across several asset pricing models and, when the prior incorporates model uncertainty, the differences between optimal portfolios across models are smaller. Uppal and Wang (2003) develop a model in which ambiguity about the distribution of returns varies across stocks. They show that small differences in individual ambiguity can substantially change asset allocations. Maenhout (2004) directly incorporates a preference for robustness in the utility function, which decreases equity holdings and increases precautionary savings.

3 Empirical implementation

The empirical analysis of the contribution of macroeconomic uncertainty to the cross-section of option returns is based on a factor model, which is estimated with the Fama-MacBeth methodology. This setting imposes little structure on the data, and reduces the potential for model misspecification problems, which can attribute risk premia to factors that are actually not priced (Broadie, Chernov and Johannes (2007a)). On the other hand, option returns are non-linear with respect to returns on the underlying, and this can bias the estimates of a linear model (see Broadie, Chernov and Johannes (2007b)).

The empirical analysis also needs to account for the microstructure of option markets, which may affect the results mainly because of non-synchroneity and measurement error in option prices. Non-synchroneity can arise because OptionMetrics, the source of option prices for this study, does not provide information on the exact time of the last trade, which may have taken place at any time during the day. The consequence is that a *daily* return may actually be a "$evening_{t-1}$ to $morning_t$" or a "$morning_{t-1}$ to $evening_t$" return. In the case of hedged returns, option prices can also be non-synchronous with stock prices. Measurement error, on the other hand, is related to the computation of option prices from the bid and ask quotes reported by OptionMetrics. A common assumption is that an option's price is the midpoint of the bid-ask spread but, if this is not the case, calculated prices are noisy estimators of true prices.

I take several steps to make sure that the results are not driven by the distributional and microstructure properties of option returns.

First, the analysis is based on both holding and delta-hedged returns. In the case of holding returns, which are generated by buying an option and holding it for a week, the longer horizon reduces the relative incidence of measurement noise on observed returns. In addition, non-synchroneity is greatest when the reported closing price is actually the opening price, and this error is a smaller fraction of the holding period with weekly rather then daily returns. Hedged returns, on the other hand, are useful to reduce the effect of non-linearity. They are based on buying an option and, at the same time, selling the Black-Scholes replicating portfolio, calculated with the deltas provided by OptionMetrics. Hedged returns are computed every day, and then averaged on a weekly basis, because delta-hedging requires frequent rebalancing. I do not use more complex hedging strategies, like delta-vega-hedging, that explicitly accounts for stochastic volatility, because they require the estimation of additional parameters, like correlations between stock and volatility innovations. Given the large number of underlying stocks and the potential for time variation, estimating correlations may actually exacerbate concerns of model misspecification. Omitted variables in the computation of hedged returns are captured in the

Fama-MacBeth regressions, which include a large set of relevant factors.

Second, I use *portfolios* as test assets, rather than individual options, to weigh down outliers and average-out individual options' non-synchroneity. Third, second-stage regressions include variables that proxy for measurement error. Fourth, a set of regressions include squared factors, to address non-linearity in the time-series relation between option and market returns, and second-stage regressions are either estimated with Weighted Least Squares or include moneyness dummies, to account for the cross-sectional heteroskedasticity generated by non-linearity (out-of-the-money options are less sensitive to market returns than in-the-money ones). A simulation confirms that, when including squared terms and moneyness dummies, Fama-MacBeth's $\hat{\lambda}s$ (the coefficients from second-stage regressions, see Section 4) accurately estimate factor risk premia. Duarte and Jones (2007), in their study of the volatility risk premium, also use simulations to show that the Fama-MacBeth approach produces accurate risk premia estimates.

3.1 Data description

Daily option prices, together with additional variables like option volume, stock prices and interest rates, are from OptionMetrics, which covers all U.S. exchange-traded index- and equity-options. The Fama-French, momentum and Pastor-Stambaugh liquidity factors, and stock bid-ask spreads are from CRSP. Intradaily returns on the Dow Jones Industrial, which are used to estimate market skewness and kurtosis with greater accuracy, are from Global Financial Data, and the VIX series is from the Chicago Board of Options Exchange. VIX is a daily index of implied volatility, based on S&P500 option prices, and is often used as a proxy for expected market volatility. Days of scheduled releases for the Consumer price index, the Employment situation, Real earnings, the Producer price index and Productivity and costs are from the Bureau of Labor Statistics. The sample includes 11.5 years, from January 1996 to June 2007.

As is customary with option data, I apply a series of filters to eliminate illiquid prices and recording errors. Table 1 shows the average number of monthly observations, by year, before and after the filters. The database grows substantially between 1996 and 2007, with a temporary reduction after 2000, and it includes almost 390 million entries. The requirement of non-zero trading volume eliminates many observations, but it is important to have option prices that reflect information from a recent transaction, which is not the case without trades on the day. I only keep options on common stocks and with standard settlement (e.g., investors are sometimes able to deliver securities other than the underlying). All equity options have American exercise, but I delete those with a missing exercise style flag because additional data fields may be incorrectly recorded. Other filters eliminate database errors, and the number of remaining observations is more than 60 million.

3.2 Options portfolios

This section has three parts. The first explains how portfolios are formed, the second discusses the two sets of returns that are used in the empirical analysis, and the third reports summary statistics.

3.2.1 Definition of option portfolios

Many option pricing studies have focused on index options, largely because of data availability and market liquidity. I have decided to use equity options because stock characteristics are useful to create dispersion in options' sensitivities to macroeconomic uncertainty.

I build option portfolios by sorting individual options across three stock and three option characteristics. Size and book-to-market are a common way of sorting stocks, because they are well-known sources of empirical regularities. They may also create dispersion in option returns' sensitivity to macroeconomic uncertainty, because Barinov (2007) shows that the value effect is related to the real option nature of growth stocks, which makes them particularly sensitive to uncertainty. OptionMetrics, however, is not representative of CRSP, especially in terms of size. I then sort options on the basis of the underlying's sensitivity to the three Fama-French factors, because HML and SMB are strictly related to the book-to-market and size effects. Sensitivities are computed by regressing daily stock excess returns on the Fama-French factors for each year from 1995 to 2006, and stocks are then sorted into factor betas tertiles. The sorting based on year t's betas applies to year $t + 1$.

Options are also sorted into portfolios on the basis of the following contract characteristics: moneyness, maturity and exercise (call/put). Moneyness should be especially useful to create dispersion in the sensitivity to macroeconomic uncertainty, because several authors have already linked the effect of uncertainty about state variables to the volatility smile (Buraschi and Jiltsov (2006), David and Veronesi (2002) and Liu, Pan and Wang (2005)). In particular, letting K be the strike price and S the stock price, I sort options into five moneyness categories:

$$MonDummy_t = \begin{cases} \text{Put} & \text{Call} & \\ 1 & 5 & -0.200 < ln(K/S_{t-1}) \leq -0.100 \\ 2 & 4 & -0.100 < ln(K/S_{t-1}) \leq -0.025 \\ 3 & 3 & -0.025 < ln(K/S_{t-1}) \leq 0.025 \\ 4 & 2 & 0.025 < ln(K/S_{t-1}) \leq 0.100 \\ 5 & 1 & 0.100 < ln(K/S_{t-1}) \leq 0.200 \end{cases}$$

Options with time to maturity between 15 and 90 (calendar) days at time $t-1$ are assigned to $MatDummy = 1$, while those with 90 to 360 days to maturity belong to $MatDummy = 2$. Options that do not fall into a moneyness and maturity category are discarded. Excluding deep out-of-the-money/in-the-money and very long/short maturity options may create concerns of sample selection. Generally speaking, it is quite common to apply criteria aimed at reducing econometric problems due to outliers and at eliminating thinly-traded options. Studies that use tick data sometimes focus on options that trade in a specific minute of the day (Constantinides, Jackwerth and Perrakis (2006)). The simulation results I present in Section 5.1 are based on the sample selection criteria described above, and show that my variables of interest are accurately estimated.

3.2.2 Definition of returns

The empirical analysis is based on two sets of returns: weekly holding returns and the weekly average of daily hedged returns. I compute weekly holding returns for each equity option, and the portfolio return on a given week is the equally-weighted return of all the options that belong to it at time $t-1$. Weekly holding returns are useful to minimize the effect of non-synchroneity and measurement error. First, the longer horizon reduces the relative incidence of measurement noise on observed returns. Second, non-synchroneity is at its maximum when the closing price is actually the opening price, and this error is a smaller fraction of the holding period with weekly rather then daily returns. In addition, and unlike hedged returns, the computation of weekly holding returns does not depend on a specific option pricing model to calculate hedge ratios. Holding returns are measured on Tuesdays, following Coval and Shumway (2001).

Holding returns, on the other hand, require the existence of valid option prices on the same weekday for consecutive weeks, which reduces the number of available observations. To address this issue, the analysis is also based on hedged returns, generated by a strategy that buys an option and sells the corresponding replicating portfolio, computed with the hedge-ratio provided by OptionMetrics. Hedged returns are measured at daily frequencies because replicating portfolios have to be rebalanced often, in order not to compromise replicating accuracy. Hedged returns are computed for each equity option, and the daily return of a portfolio is the equally-weighted average of the hedged returns of all the options that belong to it. The weekly hedged return of an option portfolio is the average of its daily hedged returns within a week. For hedged returns, the analysis is based on factors measured on Friday rather than on Tuesday, as an additional robustness check.

More in detail, weekly holding returns are defined as:

$$r_t^i = \frac{OP_t^i - OP_{t-1}^i}{OP_{t-1}^i} \tag{1}$$

where OP_t^i is the price of option i at time t. The return on a particular option portfolio, A, is the equally weighted return of all the options that belong to it at time $t-1$:

$$r_t^A = \frac{1}{\#A_{t-1}} \sum_{i \in A_{t-1}} r_t^i \tag{2}$$

Daily hedged returns for option i are:

$$r_s^{\Delta,i} = \frac{OP_s - OP_{s-1} - \Delta_{s-1}(S_s - S_{s-1}) + (1 + r_{s-1}^f)\Delta_{s-1} S_{s-1}}{OP_{s-1}} \tag{3}$$

where Δ is the hedge-ratio provided by OptionMetrics, S the stock price and r^f the shortest maturity riskless rate. The time subscript is s rather than t to emphasize that these are *daily* returns. Portfolio A's daily hedged return is the equally weighted hedged return of all the options that belong to it at the beginning of the week:

$$r_s^{\Delta,A} = \frac{1}{\#A} \sum_{i \in A} r_s^{\Delta,i} \tag{4}$$

and the weekly portfolio hedged return is the average of daily portfolio hedged returns:[9]

$$r_t^{\Delta,A} = \frac{1}{5} \sum_{s \in [t-1,t]} r_s^{\Delta,A} \tag{5}$$

3.2.3 Returns statistics

Table 2 shows summary statistics for option portfolios' weekly holding returns, averaged across different portfolio characteristics. Sorting by moneyness produces the most evident pattern, with out-of-the-money options earning almost 7% a week, and in-the-money ones losing about 10% a week. Short maturity options and puts also lose about 1.5% and 3% a week. When it comes to stock characteristics, portfolios with low sensitivity to the market, SMB and HML factors lose between 0.50% and 1%.

To gauge the extent of non-linearity in the time-series relation between option portfolio returns and market returns, Figures 1 and 2 plot returns on a call and a put option portfolio against market returns. Both portfolios have high sensitivity to the market, low sensitivity to HML and SMB, short maturity, and include at-the-money options,

[9] By averaging first across days and then across weeks, the return has an equally-weighted portfolio interpretation. For both weekly and hedged returns, I drop options on stocks that pay dividends during the returns calculation period. The fraction of options deleted with this filter is negligible. I also winsorize the sample of individual option returns at 0.5% and the sample of option portfolios returns at 1%. I have tried several other symmetric and non-symmetric cutoffs, without altering the conclusions. For hedged returns, I also drop daily returns in excess of 25%. The reason is that arithmetic returns have the option price at the denominator, and when this is small and the hedged payoff is large in absolute value, the return is extreme. I have also winsorized at 30% and 20%, without changes in the results.

for which non-linearity is more pronounced (at-the-money options have a large gamma, which is the second derivative of the option price with respect to the underlying's price).

Figure 1 shows returns on the portfolio of call options, together with two regression lines. One is calculated from standard OLS, while the other is computed by weighing down observations that generate non-linearity. More specifically, observations corresponding to the bottom 25% of market returns receive a weight of 0.25 in the Weighted Least Squares regression, rather than 1. The reason for doing so is apparent in the leftmost portion of Figure 1. When call options are at-the-money, high market returns (routed through returns on the underlying stocks) translate into higher option returns. On the other hand, low market returns do not generate correspondingly low option returns, because the value of a call option rapidly falls toward zero. Indeed, Figure 1 shows that the relation between option returns and market returns is almost a flat line for low market returns, while it is positively sloped for high returns. By weighing down the bottom 25% of market returns, I can evaluate the impact of non-linearity on the estimated market beta. The plot suggests there is a slight difference in the estimated slopes, with the market beta being larger when non-linearity is accounted for. More in detail, the standard OLS regression gives a market beta equal to 9.99 (with a standard error of 0.33) and an intercept of -0.009 (0.008), while Weighted LS estimates the slope at 10.60 (0.46) and the intercept at -0.011 (.009). The percentage difference between estimated betas is -5.8%.

Figure 2 repeats the analysis described above for the put option portfolio. In this case non-linearity is generated by high market returns, because the price of a put option quickly declines toward zero, so the weight of 0.25 applies to observations with market returns in the last quartile. Standard OLS estimates are equal to -10.32 (standard error 0.37) for the market beta, and -0.030 (0.008) for the intercept. In the case of Weighted

LS, beta is equal to -11.31 (0.47) and the intercept to -0.036 (0.010), giving a percentage difference of -8.8% between estimated betas.

The results above suggest that, while the non-linearity of option returns with respect to the market affects time-series OLS estimates, the effect is relatively small. In addition to the robustness checks discussed in Section 5, I have run the Fama-MacBeth estimation with the weighing scheme defined above applied to all option portfolios, and the conclusions described in Section 4 are unaffected.

3.3 Macroeconomic uncertainty factor

The macroeconomic uncertainty factor is built in three steps. First, I identify days when macroeconomic uncertainty is higher. Second, I find options that have *unusual* prices on such days, which is evidence that they are more sensitive to macroeconomic uncertainty. These options are identified on the basis of normalized pricing errors, to be defined shortly. Third, I form a factor mimicking portfolio that sells options with low normalized pricing errors and buys options with high normalized pricing errors.

3.3.1 Days of higher macroeconomic uncertainty

As discussed in Section 2.2, stock, bond and option prices react quickly to macroeconomic announcements, which is evidence of a resolution of uncertainty immediately after the release of economic news. Furthermore, Beber and Brandt (2007) and Savor and Wilson (2008) analyse, respectively, the behavior of equity implied volatilities and interest rates around macroeconomic announcements, and suggest that investors increase their hedging activity and precautionary savings before scheduled announcements, which is also consistent with higher uncertainty.

On the basis of these results, I define day t as a day with higher macroeconomic uncertainty if there is a scheduled announcement on day $t + 1$. The analysis is based on announcements about five variables, chosen to span news about the monetary, occupational and industrial outlooks: the Consumer price Index, the Employment situation, Real earnings, the Producer price index and Productivity and costs.

3.3.2 Option prices on days of higher macroeconomic uncertainty

Options with greater sensitivity to macroeconomic uncertainty are identified by analysing Black-Scholes pricing errors on pre-announcement (or *pre-news*) days, normalized by subtracting the median pricing error on non pre-news days. The rationale behind this approach is that, if an option is more sensitive to macroeconomic uncertainty, its price should change more when macroeconomic uncertainty increases. As a consequence, one could infer the sensitivity by comparing the average price of an option on pre-news days with the average price on non pre-announcement days. This, however, would not take into account that option prices also depend on several additional variables, first of all underlying prices, interest rates and time to maturity. By focusing on pricing errors, I isolate the component of option prices that is not explained by a number of variables already known to be important for option pricing. The Black-Scholes models omits several of the features of more recent models, like stochastic volatility and jumps, which of course will be reflected in the pricing errors. The use of a simpler model, however, minimizes the possibility that macroeconomic uncertainty is proxied by one of the higher moments in a jump-diffusion setting, given that more general models are more prone to misspecification and to mis-attributing risk premia (Broadie, Chernov and Johannes (2007a)). To avoid, on the other hand, that macroeconomic uncertainty proxies for omitted variables, the Fama-MacBeth regressions include a large set of relevant factors, like stochastic volatility and higher moments.

To summarize, I isolate the contribution of macroeconomic uncertainty to option returns in three steps. When building the factor, I compute Black-Scholes pricing errors, which eliminate the effect on option prices of a small but very important set of variables, and I focus on days when the relative importance of macroeconomic uncertainty for option pricing errors is greater. In the empirical analysis, I include a large set of relevant factors that control for the variables omitted in the computation of the Black-Scholes pricing errors.

3.3.3 Detailed construction of the macroeconomic uncertainty factor

The procedure for constructing the macroeconomic uncertainty factor is as follows. First, I compute pricing errors (PE) for all options, on each day:

$$PE_{i,t} = \ln \frac{abs\left(BS_{i,t} - SBS_{i,t}\right)}{OP_{i,t}} \tag{6}$$

where $BS_{i,t}$ is the option's Black-Scholes price computed with the previous 30 days' realized volatility, $SBS_{i,t}$ is the Black-Scholes price computed with OptionMetrics' implied volatility[10] and $OP_{i,t}$ is the option's bid-ask midpoint. I then calculate the daily PE for each option portfolio, $PE_{p,t}$, as the median $PE_{i,t}$ across all the options belonging to p.

Next, I collect scheduled announcement dates for the Consumer price index, the Employment situation, Real earnings, Producer price index and Productivity and costs.

[10] This implied volatility is calculated using a binomial tree based on the Cox-Ross-Rubinstein model. See the OptionMetrics Data Reference Manual for more details.

For each option portfolio, in each quarter, I define the *Excess PE* (*EPE*) as the absolute value of the difference between the median PE on pre-news days and the median PE on normal days. More precisely, the EPE for portfolio p in quarter q is:

$$EPE_{p,q} = abs(\bar{PE}_{p,q}^{pre\text{-}news} - \bar{PE}_{p,q}^{normal}) \tag{7}$$

where $\bar{PE}_{p,q}^{pre\text{-}news}$ is the median PE on days immediately before scheduled news releases, and $\bar{PE}_{p,q}^{normal}$ is the median PE on non pre-announcement days.

I then sort option portfolios into quintiles on the basis of their *EPE*.[11] The *EU* factor is the difference between the median return of the "high EPE" and of the "low EPE" quintiles.

Figure 3 plots the time series of the S&P500's end-of-quarter level, and of the quarterly average of the macroeconomic uncertainty factor. The factor spikes around the end of 2002, and is also relatively high during 1999 and 2000. While the sample includes only two turning points in economic growth, namely 1999/2000 and 2002/2003, the factor is high when the economy is about to enter a phase of expansion or contraction, while it stays closer to the mean when the business cycle's trend is consolidated, whether it is positive or negative.

Figures 4 and 5 give an insight on which options are included in the high/low EPE quintiles. Figure 4 shows the percentage of options that belong to the high/low EPE quintiles according to whether the underlying has a low (panel 1), medium (2) and high (3) sensitivity to the market. Figure 5 has a similar structure, showing maturity categories instead of market sensitivity. As one may expect, long-dated options mostly fall in the

[11] The sorting in quarter q applies to quarter $q + 1$.

high EPE quintile. Options on stocks with high sensitivity to the market, on the other hand, mainly belong to the low EPE quintile, although not by a substantial margin.

3.4 Additional factors

As mentioned above, the *EU* factor is based on Black-Scholes pricing errors. Being residuals, pricing errors contain the effect of omitted factors. To control for this, the regressions include 13 additional factors and 4 controls that are expected to affect stock and option returns.

Asset pricing factors. *Market, SMB, HML, UMD and Liquidity.*

Weekly Fama-French factors are computed by compounding daily returns. The Pastor-Stambaugh liquidity factor is only available at monthly frequency, so I construct a factor mimicking portfolio. I sort CRSP stocks on the basis of their liquidity beta, computed by regressing monthly excess returns on the Market, SMB, HML, UMD and on innovations to the Pastor-Stambaugh liquidity factor (Pastor and Stambaugh (2003)). The regressions cover the 1996-2004 period. Stocks are sorted into quintiles on the basis of their liquidity beta, and the factor is the difference between the equally weighted returns on stocks in the fifth and in the first quintile.

Option pricing factors. *Volatility, Volatility of volatility, Skewness of volatility, S&P 500 put returns, Volatility of S&P 500 put returns, Skewness of S&P 500 put returns, Market skewness, Market kurtosis.*

The *Volatility* factor is the series of weekly changes in the VIX index. *Volatility of volatility* and *Skewness of volatility* are changes in the weekly volatility and skewness of daily VIX changes. *S&P 500 put returns* is the weekly average of daily returns on S&P 500 put options with $-0.2 < ln(K/S) < -0.1$. *Volatility and Skewness of S&P 500 put returns* are changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 options, as defined above. *Market skewness* and *Market kurtosis* are weekly changes in the skewness and kurtosis of intradaily Dow Jones Industrial returns.

Table 3 provides time series summary statistics for the 14 factors used in this paper. Out of the Fama-French, momentum and liquidity factors only HML and UMD have statistically significant average returns. Volatility and Put factors also have non-statistically significant mean changes, with the exception of returns on out-of-the-money index puts. The *EU* factor has a positive and statistically significant mean, although it can not be properly interpreted as an equally weighted portfolio strategy because it is based on median returns. Table 4 reports correlations among the factors. The market is highly correlated with changes in VIX, which is a well-known fact. Similarly, the -56% correlation between Mkt and Put is expected. The economic uncertainty factor, on the other hand, has very low correlations with all the other factors.

4 Results

The empirical analysis is based on the time-series and cross-sectional regressions method of Fama and MacBeth (1973). As discussed in section 3, this choice is meant to impose little structure on the data, and to reduce the potential for model specification issues. The time series (first-stage) regressions are:

$$r_t^k - r_t^f = \alpha_{1,k} + \sum_{i=1}^{n} \beta_{i,k} f_{i,t} + \varepsilon_{k,t}, \forall k \tag{8}$$

where r_t^k is the weekly return on the option portfolio k and $f_{i,t}$ is one of the n demeaned factors.

The cross-sectional (second-stage) regressions are:

$$r_t^k - r_t^f = \alpha_{2,t} + \sum_{j=n+1}^{n+m} \lambda_{j,t} Cont_{j,t} + \sum_{i=1}^{n} \lambda_{i,t} \hat{\beta}_{i,k} + \epsilon_k, \forall t \quad (9)$$

where $Cont_{j,t}$ are controls for measurement error in stock and option prices (relative stock and option bid-ask spreads), hedging risk borne by option market-makers (log-vega and log-gamma) and the underlying's exposure to macroeconomic uncertainty (its beta from time-series regressions). The controls are median $t-1$ values computed across all the options that belong to a given portfolio. To account for the effect of option returns' non-linearity on the estimated Fama-MacBeth second-stage coefficients, a set of regressions also include squared factors and moneyness dummies, as discussed in the robustness checks section. The contribution of factor f to the cross-section of option returns is estimated as the time-series average of the coefficients from the T cross-sectional regressions:

$$\hat{\lambda}_f = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_{f,t} \quad (10)$$

The regressions are run on weekly returns from the second quarter of 1996 - the first is used to sort options into high/low EPE portfolios - until the end of the sample in June 2007. All t-stats are Newey-West- (4 lags) and Shanken-adjusted.

Table 5 reports estimated $\hat{\lambda}s$ for weekly holding excess returns. Measurement error controls have positive $\hat{\lambda}s$, which is expected because measurement error positively biases observed returns (Blume and Stambaugh (1983)). $\hat{\lambda}_\gamma$ is not statistically significant, but $\hat{\lambda}_\nu$ is positive and strongly significant, which is consistent with the hypothesis that market makers (who have net positive holdings of equity options) require compensation to hold options that are more difficult to hedge (Gârleanu, Pedersen and Poteshman (2007)).

The underlying's beta with respect to EU has a mostly insignificant $\hat{\lambda}$, which means that macroeconomic uncertainty exerts a specific effect on options, that is not routed through returns on the underlying. It is positive, though, which is consistent with the sign of $\hat{\lambda}_{EU}$ and also with the results of Anderson, Ghysels and Juergens (2007). The intercept is positive and significant, both economically and statistically. I discuss this in more detail in the robustness checks section, where I evaluate the effect of option returns' non-linearity on the results.

$\hat{\lambda}_{Mkt}$ is positive and larger than the time series average of Mkt, but the difference is not statistically significant. $\hat{\lambda}_{Umd}$, on the other hand, is significantly different from the time series average return on Umd. Vix is not significant in this specification, but it is equal to about -40 basis points in the others. Interestingly, Put and Put_v enter with a positive sign in specification (1), but this result is not robust when including other sets of factors. The macroeconomic uncertainty factor has a positive and significant $\hat{\lambda}$, both economically and statistically, which is remarkably stable through alternative specifications. Its magnitude is substantial, but the corresponding betas from time-series regressions range from about -0.40 to 0.50, and the contribution of macroeconomic uncertainty to expected excess returns is about 50% a year for the option portfolio with the 75^{th} percentile β_{EU}. This compares with an average return on out-of-the-money option portfolios equal to 6.81% a week, or more than 300% a year. Lastly, first and second-stage adjusted R^2s (averaged across all time series and cross-sectional regressions, respectively) are about 40% and 50%, and adding EU to the full set of factors and controls increases $\bar{R}^2$ by 0.70%. By comparing the $\bar{R}^2$ of specification (1) with those of specifications (2) and (3), it's clear that the contribution of EU is similar to that of the other factors. For instance, adding the three Fama-French factors to selected moment factors (specification (1) relative to (3)) increases the cross-sectional $\bar{R}^2$ by about 6%, and the market is obviously very important in explaining the cross-section of option returns.

5 Robustness checks

This section mainly focuses on the effect of the non-linearity of option returns, with respect to returns on the underlying, on the estimates obtained with the Fama-MacBeth method. In additional unreported robustness checks I have excluded 1996, 1997 and 1999 because exogenous events, like new listing rules and the availability of new products (see De Fontnouvelle, Fishe and Harris (2003) and Gârleanu, Pedersen and Poteshman (2007)), may have affected the results. I have also dropped options with $MonDummy = 1$, deleted weeks with $abs(EU) > 0.5$ and set non-significant first-stage betas equal to zero. In any of these cases, the conclusions are unchanged.

By construction, option returns are non-linear in returns on the underlying, and this can affect the coefficients of both first and second stage regressions. In the time series, the beta of an option with respect to the market is not constant across market returns, because an option's moneyness changes with market returns (routed through returns on the underlying stock). In the cross-section, non-linearity generates heteroskedasticity, because out-of-the-money options are less sensitive to market returns than in-the-money ones. While the results in Section 3.2.3 show that the non-linearity bias is not of first order importance for time-series betas, I take several steps to account for non-linearity. More specifically, I include squared terms in time-series and cross-sectional regressions, and I estimate second stage regressions by either adding moneyness dummies or using Weighted Least Squares.

The first robustness check deals with non-linearity by adding the squared value of a selected group of factors to both the time-series and cross-sectional regressions. The choice of which squared factors to include is not discretionary, but is determined as follows. For every option portfolio, I find the polynomial regression, among those with factors raised to the power 1 and 2, that best describes the time series of returns, and for each factor I compute the percentage of portfolios in which the best-fitting regression includes a squared term. If the percentage is greater than 5%, the squared factor is included in the Fama-MacBeth estimation. The best fitting time-series regression is the one with the lowest $D = n(1 + ln\frac{2\pi RSS}{n})$, where n is the number of observations and RSS the residual sum of squares. Interestingly, only three factors exceed the 5% threshold (Table 12), namely Mkt, Hml and Umd, and only Mkt does so by a substantial margin (25%).

Table 6 reports the results of the Fama-MacBeth estimation that includes squared Mkt, Hml and Umd in first and second-stage regressions. The intercept is noticeably lower, but still positive and significant, and $\hat{\lambda}_{Mkt}$ is now virtually identical to the time-series average. The volatility factors are not significant (with the exception of specification (3), which is the same as in Table 5, because it does not include any Mkt, Hml and Umd terms), while $\hat{\lambda}_{Put}$ and $\hat{\lambda}_{Put_v}$ are positive and significant, especially $\hat{\lambda}_{Put_v}$. The macroeconomic uncertainty factor still enters significantly, and $\hat{\lambda}_{EU}$ is actually slightly larger than in Table 5 for specifications (1) and (2).

In cross-sectional regressions, I address heteroskedasticity by either including moneyness dummies or using WLS. In the first case, the dummies are for $MonDummy = 1, 2, 3$, i.e. from deep out-of-the-money to at-the-money[12] and for put/call contracts. Table 7

[12] I have also repeated this section's robustness checks with dummies for $MonDummy = 3, 4, 5$, i.e. from at-the-money to deep in-the-money. The intercept changes sign, but it is still statistically insignificant, while other results are unaffected.

shows that the dummies have an effect on several results (relative to Table 6). $\hat{\lambda}_{os}$ is now about ten times smaller, and even statistically insignificant in specifications (1) and (4), which suggests that most of the measurement error in option prices is found in out-of-the-money options. $\hat{\lambda}_{\gamma}$ is larger and strongly significant, while Put factors are rendered statistically insignificant. The coefficient on the macroeconomic factor is also smaller, at about 5% per week, but still positive and significant. In this case, macroeconomic uncertainty increases the expected return on a portfolio with the 75^{th} percentile β_{EU} by about 40% a year. Unreported results show that first-stage betas on *EU* are larger for out-of-the-money options, especially calls, so moneyness dummies are expected to capture part of macroeconomic uncertainty's effect on returns. Finally, the intercept is now statistically insignificant across all specifications. As discussed in Section 5.1, adding moneyness dummies eliminates the non-linearity bias also in simulated data, where the dummies are not proxying for any omitted factors by construction. Table 8 reports estimated $\hat{\lambda}s$ when the specifications include moneyness dummies and squared terms for *all* factors. The additional factors don't have a substantial effect on the results, with the exception of $\hat{\lambda}_{Vix_v}$, which is now non-significant, and of the cross-sectional $\bar{R}^2$s, which increase by about 5%.

Table 9 shows risk premia when the macroeconomic uncertainty factor only includes options on cyclical and non-cyclical stocks.[13] The risk premium on macroeconomic uncertainty is lower for non-cyclical stocks, as it could be expected, although the difference is statistically weak. The market risk premium is also greater when *EU* is built with cyclical stocks, while the volatility risk premium is significantly negative only when *EU* is based on non-cyclical stocks.

[13] Stocks are classified according to the industry growth betas estimated by Boudoukh, Richardson and Whitelaw (1994), where available. Cyclical stocks are those with the first two SIC code digits equal to: 22, 25, 30, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 61, 62, 70, 72, 73, 75, 76, 78, 79, 82, 83, 84, 86, 87, 88, 89. Non-cyclical stocks are those with different first two SIC code digits.

Table 10 reports the risk premia when cross-sectional regressions are estimated by Weighted Least Squares. Breusch-Pagan tests show that heteroskedasticity is related to the option spread, os,[14] and the weighting function is the inverse of the fitted portfolio return squared, as predicted by os. The risk premium attached to EU is positive and statistically significant, while the intercept is statistically equal to zero, and the cross-sectional average $\bar{R}^2$ is considerably higher than under alternative specifications. Panels (2) and (3) show the results of a subperiod analysis, where the samples include 1996-2001 and 2002-2007. Besides being a robustness check in its own right, the comparison between Panels (2) and (3) is interesting because Economic Derivatives where marketed during 2002-2007, which implies that investors were able to trade directly on uncertainty about macroeconomic variables. As one would expect, the risk premium estimated over the more recent period is smaller than when Economic Derivatives were not available.

The final robustness check uses excess hedged returns as the dependent variable, and the results are reported in Table 11. The specifications are equivalent to those in Table 5, in that they do not include dummies nor squared terms. Interestingly, the intercept is still positive and significant, but it is about five to ten times smaller than in Table 5. This, too, supports the hypothesis that the intercept is different from zero because of the effect of option returns' non-linearity, rather than because of omitted factors. The Fama-French factors do not enter significantly, with the exception of specification (2), where they are probably proxying for the omitted volatility factor. $\hat{\lambda}_{Umd}$ and $\hat{\lambda}_{Liq}$, however, are both significant even with the full set of factors. The coefficient on Vix is strongly significant, as is the one on Vix_v, and also larger than in specifications based on holding returns, but time-series betas on Vix are smaller than in the case of holding returns.

[14] The variable os is monotonically increasing in moneyness, being higher for out-of-the-money options.

5.1 Simulation

Option returns are non-linear in the underlying's returns, and this can bias the estimates of linear factor models (see Broadie, Chernov and Johannes (2007b)). In order to account for non-linearity, I have included squared factors and dummies in first and second-stage regressions, as described in the previous section. I now use a simulation to evaluate whether this approach generates accurate estimates of factor risk premia.

I simulate returns on 50 assets using a single factor model, and then compute Black-Scholes returns on several options on each asset. Following the empirical analysis discussed above, I form option portfolios on the basis of moneyness, maturity, put/call contract type and stock sensitivity to the single factor (or *market*). While the Black-Scholes model is relatively simple and omits factors like volatility and jumps, the simulation is meant to analyse the effect of option returns' non-linearity, and this can be accomplished with a single factor model. Tellingly, Table 12 shows that, in the actual data, Mkt is the only factor for which a squared term clearly improves the fit of the regressions.

The focus is on the results from second-stage regressions:

$$r_t^k - r_t^f = \alpha_{2,t} + \sum_{i=1}^{n} \lambda_{mkt,t} \hat{\beta}_{mkt,k} + \epsilon_k, \forall t \tag{11}$$

where $\hat{\beta}_{mkt,k}$ is the time-series beta estimated in first-stage regressions. I test whether the estimated market risk premium, $\hat{\lambda}_{mkt}$, is statistically different from the risk premium used to generate stock returns, and if the intercept $\hat{\alpha}_2$ is different from zero.

Simulated option returns have weekly frequency, for a total of 11.5 years. The simulation is run twice, with two values for the market risk premium (0% and 10%). The riskless rate and the volatility of the market are constant, at 3% and 18% year. Asset betas and volatilities match the range of the corresponding variables in the sample, with betas starting at 0.4 and up to 1.9, while annualized volatilities are between 20% to 95%. Every week I compute Black-Scholes prices for call and put options with maturity of 2 and 7 months, and moneyness $ln(K/S)$ equal to -15, -6.25, 0, 6.25, 15%. These values are the mid-points of the moneyness and maturity intervals defined in section 3.2.2. I then form option portfolios by intersecting the following characteristics: underlying stock's beta with respect to the market (10 deciles), moneyness (5 categories), maturity (2) and call/put type (2). Weekly portfolio returns are the equally weighted average of the constituent options' returns. To reduce the effect of outliers on the results, I winsorize option returns at both the option and portfolio level with cut-offs of, respectively, 0.175% and 0.35%. These are a fraction (35%) of the cutoffs used in the empirical analysis, because simulated returns are not affected by measurement error and non-synchroneity.

Table 13 reports the average $\hat{\lambda}_{mkt}$ and $\hat{\alpha}_2$ across the 1,000 replications, along with 90% confidence intervals based on bootstrapped standard errors. The results suggest that, after accounting for option returns' non-linearity, the Fama-MacBeth method accurately estimates option risk premia. More precisely, when the risk premium is equal to 10%, both $\hat{\alpha}_2$ and $\hat{\lambda}_{mkt}$ are not statistically different from their true values (0% and 10%). For a zero risk premium, on the other hand, $\hat{\lambda}_{mkt}$ is negatively biased by about 36 basis points a year. The 95% confidence interval, however, does include zero.

6 Conclusions

I study whether macroeconomic uncertainty is a priced risk factor in the cross-section of option returns. I do so by using a factor model, estimated with the Fama-MacBeth methodology, in order to impose little structure on the data.

The macroeconomic uncertainty factor is based on option pricing errors, computed on days immediately before scheduled announcements of macroeconomic news, and normalized by subtracting the median pricing error on non pre-announcement days. The factor is the return generated by a trading strategy that buys and sells options according to whether their normalized pre-announcement pricing errors are high or low.

Option returns are non-linear with respect to returns on the underlying, and this may bias the estimates of linear factor models. I account for the non-linearity of option returns with a series of controls in time-series and cross-sectional regressions, and a simulation confirms that this approach produces accurate estimates of the risk premia.

I find that macroeconomic uncertainty explains the cross-section of option returns, and this result is also robust to measurement error in stock and option prices, and to a large set of relevant factors, which include stochastic volatility, jumps and higher moments.

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Figure 1. Market returns, and returns on the at-the-money call option portfolio with the highest sensitivity to Mkt (third tertile), short maturity and low sensitivity to SMB and HML (first tertile). One regression line is from standard OLS, the other is from WLS, where observations with market returns below the 25% percentile (-0.012) are assigned a weight of 0.25.

Figure 2. Market returns, and returns on the at-the-money put option portfolio with the highest sensitivity to Mkt (third tertile), short maturity and low sensitivity to SMB and HML (first tertile). One regression line is from standard OLS, the other is from WLS, where observations with market returns above the 75% percentile (0.015) are assigned a weight of 0.25.

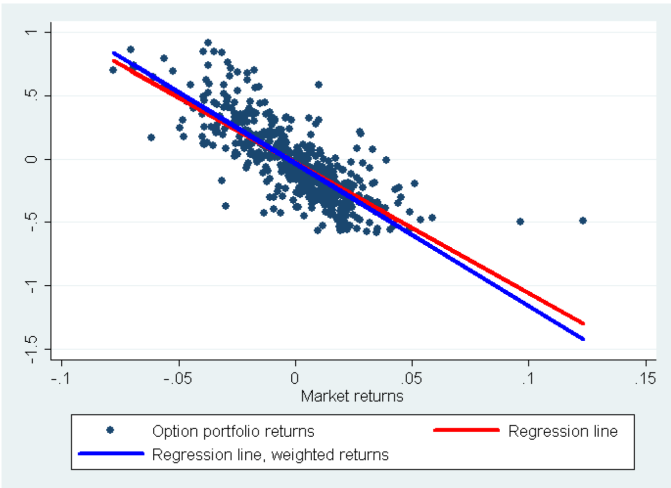

Figure 3. Quarterly average of the EU factor and end-of-quarter level of the S&P500. 1996(q2) to 2007(q2).

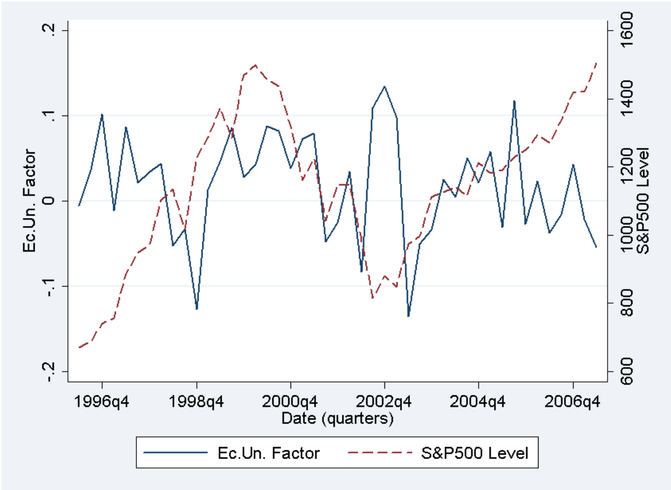

Figure 4. Percentage of option portfolios belonging to the high/low EPE quintiles, according to whether the underlying has a low (panel 1), medium (2) and high (3) sensitivity to Mkt.

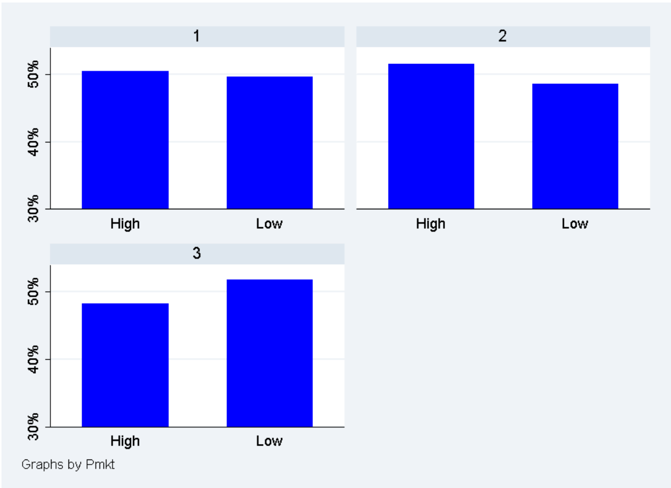

Figure 5. Percentage of option portfolios belonging to the high/low EPE quintiles, according to maturity (panel 1 - Short maturity, panel 2 - Long maturity).

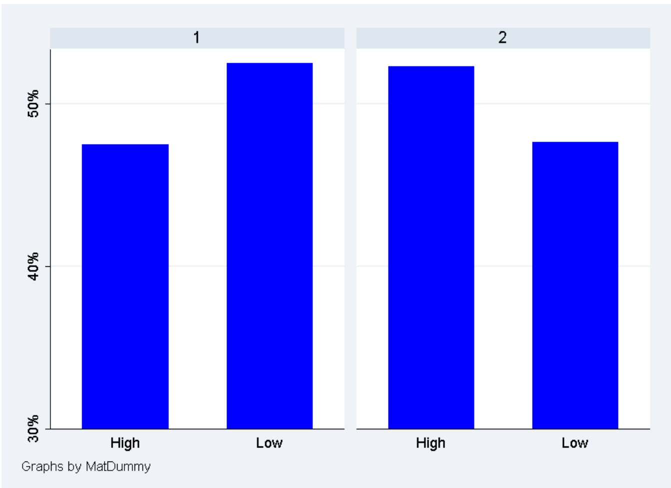

Table 1: Average number of monthly observations, by year.

The table reports the average number of monthly observations before and after a series of filters. Figures and percentages are rounded to the nearest integer. 1996(Jan) to 2007(Jun). Filters drop observations as follows. (1) An option identifier refers to more than one option series. (2) Volume is equal to zero. (3) Bid or ask price is equal to zero. (4) Ask price greater than bid. (5) Contract is non-standard. (6) Underlying is not a stock. (7) Exercise style is European or unspecified.

Year	Total	ID unique (1)	Non-zero volume (2)	Non-zero ask/bid (3)	Ask> bid (4)	No special settlement (5)	Stock options (6)	American exercise (7)	Used as % of total
1996	1,218,015	1,218,015	219,275	213,996	213,580	211,878	206,488	206,488	17%
1997	1,777,007	1,777,007	276,877	270,572	270,190	266,594	259,326	259,326	15%
1998	2,197,941	2,197,941	331,838	323,959	322,766	315,602	305,768	305,768	14%
1999	2,489,147	2,489,147	420,261	411,388	409,160	401,198	387,729	387,685	16%
2000	3,156,323	3,155,881	603,607	589,670	579,924	568,110	545,233	545,218	17%
2001	2,688,616	2,686,705	447,577	432,050	430,091	423,774	403,207	403,193	15%
2002	2,570,823	2,569,443	406,548	390,237	389,081	384,719	361,707	361,707	14%
2003	2,378,004	2,375,249	415,635	401,125	400,380	396,690	368,123	368,123	15%
2004	2,857,701	2,854,478	512,339	493,711	493,056	488,309	449,097	449,097	16%
2005	3,226,817	3,219,752	597,811	574,714	574,194	569,441	518,830	518,830	16%
2006	3,723,522	3,713,102	752,253	725,609	725,194	718,762	645,143	645,143	17%
2007	3,972,290	3,960,454	815,671	787,682	787,490	780,847	682,246	682,246	17%

Table 2: Weekly holding returns statistics.

The table reports time-series statistics of option portfolios' weekly holding returns, averaged across the specified characteristic. Returns are Tuesday to Tuesday, from 1996(q2) to 2007(q2). All figures are percentages.

		mean	**t-stat**	**10th**	**25th**	**50th**	**75th**	**90th**
Pmkt	**1**	-0.71	-3.06	-7.04	-4.53	-1.33	2.93	6.42
	2	-0.25	-0.91	-8.20	-4.81	-0.53	3.58	8.45
	3	-0.47	-1.52	-8.97	-5.36	-1.45	3.57	9.05
Psmb	**1**	-0.41	-2.08	-6.03	-3.61	-0.90	2.68	6.21
	2	-0.09	-0.20	-11.23	-5.99	-1.27	4.60	13.33
	3	-0.47	-1.52	-8.97	-5.36	-1.45	3.57	9.05
Phml	**1**	-0.92	-4.60	-6.95	-3.99	-1.08	1.81	5.01
	2	0.79	1.70	-11.19	-6.65	-0.31	7.31	15.52
	3	1.04	1.40	-17.53	-8.56	-0.75	8.02	20.76
Moneyness	**1**	6.81	15.50	-4.93	0.01	4.89	13.47	20.33
	2	0.97	3.13	-7.73	-3.91	0.44	4.96	10.19
	3	-1.09	-3.93	-9.53	-5.47	-1.12	3.14	7.61
	4	-3.48	-13.78	-11.17	-7.19	-3.50	0.32	3.88
	5	-9.47	-29.03	-19.56	-13.82	-8.51	-4.17	-1.04
Maturity	**1**	-1.42	-5.27	-9.43	-5.79	-1.87	2.50	7.45
	2	0.80	3.67	-5.84	-2.82	0.62	3.94	7.45
Style	**Call**	0.83	1.22	-20.15	-11.44	1.06	12.41	20.83
	Put	-2.70	-3.52	-23.19	-15.85	-6.50	9.33	22.97

Table 3: Factor statistics.

The table reports factor statistics. From 1996(q2) to 2007(q2). Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options.

	mean	**t-stat**	**10th**	**25th**	**50th**	**75th**	**90th**
Mkt	0.14	1.35	-2.88	-1.29	0.34	1.54	2.81
Smb	0.04	0.69	-1.57	-0.80	0.11	0.92	1.66
Hml	0.12	1.88	-1.50	-0.66	0.08	0.77	1.68
Umd	0.23	2.39	-2.08	-0.72	0.28	1.35	2.64
Liq	0.00	0.24	-0.46	-0.22	0.01	0.25	0.47
Vix	0.00	0.00	-2.57	-1.13	-0.04	1.12	2.81
Vix_v	0.00	-0.01	-0.78	-0.38	-0.02	0.33	0.86
Vix_s	0.02	0.26	-2.36	-1.09	0.12	1.04	2.36
Skew	0.00	0.00	-1.66	-0.86	0.02	0.87	1.57
Kurt	0.00	0.01	-2.60	-1.19	-0.01	1.15	2.42
Put	-5.04	-9.25	-19.48	-13.69	-6.67	0.91	11.87
Put_v	0.11	0.21	-15.33	-7.16	-0.14	7.50	15.58
Put_s	0.19	0.05	-108.41	-54.47	0.78	51.80	103.31
EU	1.79	1.94	-23.16	-9.82	1.99	14.28	26.58

Table 4: Factor correlations.

The table shows factor correlations. Weekly returns, except for Vix factors and Kurt and Skew, for which changes are reported. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options.

	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt	Put	Put$_v$	Put$_s$	EU
Mkt	1.00													
Smb	0.01	1.00												
Hml	-0.57	-0.29	1.00											
Umd	-0.16	0.21	0.06	1.00										
Liq	0.13	-0.01	-0.08	-0.07	1.00									
Vix	-0.77	0.09	0.34	0.11	-0.07	1.00								
Vix$_v$	-0.29	-0.05	0.16	0.01	-0.07	0.28	1.00							
Vix$_s$	-0.43	0.18	0.23	0.05	0.01	0.64	0.16	1.00						
Skew	0.08	-0.07	-0.08	-0.01	0.01	-0.12	0.09	-0.16	1.00					
Kurt	0.08	0.03	-0.10	-0.01	0.02	0.00	0.04	-0.08	0.20	1.00				
Put	-0.56	0.12	0.19	-0.01	-0.02	1.00								
Put$_v$	-0.20	-0.02	0.18	-0.08	-0.06	0.16	0.41	0.03	0.10	0.06	0.24	1.00		
Put$_s$	0.03	0.01	0.05	0.00	0.03	0.00	0.08	0.07	-0.04	-0.05	-0.16	0.23	1.00	
EU	-0.07	0.04	0.00	0.13	0.00	0.10	0.10	0.04	-0.02	0.04	-0.02	0.02	-0.06	1.00

Table 5: Fama-MacBeth estimation, weekly holding returns.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
(1)	0.0602	0.0088	0.0399	-0.0032	0.1952	0.0941	0.0026	-0.0014	-0.0017			-0.0021	-0.0006		0.1846	
	13.25	2.13	14.42	-1.17	1.22	5.39	2.47	-1.12	-1.61			-1.03	-0.77		0.95	
	0.0328	0.0300		0.1191		0.380	0.477									
	2.21	2.42		4.14												
(2)	0.0622	0.0090	0.0403	-0.0033	0.1766	0.1003	0.0016	-0.0017	-0.0006							
	14.54	2.58	14.66	-1.33	1.31	6.41	1.57	-1.51	-0.59							
				0.1172		0.377	0.449									
				4.84												
(3)	0.0633	0.0075	0.0401	-0.0058	0.2568	0.0908						-0.0048	-0.0001		0.4193	
	13.61	1.80	13.17	-1.83	1.62	5.33						-3.40	-0.18		2.57	
	0.0200	0.0295		0.0877		0.228	0.414									
	1.57	1.95		3.60												
(4)	0.0573	0.0060	0.0441	0.0014	0.1833	0.0850	0.0022	-0.0018	0.0004	-0.0125	0.0007	-0.0036	-0.0016	-0.0004	-0.0211	0.4472
	12.40	1.48	13.78	0.47	1.15	4.78	2.22	-1.51	0.43	-4.71	1.33	-1.79	-1.91	-0.20	-0.11	1.64
	-0.0085	0.0224	-0.1828			0.382	0.500									
	-0.59	1.57	-1.67													
(5)	0.0539	0.0069	0.0416	0.0011	0.1710	0.0836	0.0011	-0.0029	-0.0005	-0.0140	0.0003	-0.0043	-0.0017	-0.0021	0.0819	-0.0296
	10.14	1.39	11.62	0.30	0.91	3.91	1.08	-2.09	-0.42	-4.53	0.45	-1.80	-1.63	-0.88	0.36	-0.09
	0.0175	0.0189	-0.2447	0.1542		0.387	0.507									
	0.99	1.18	-2.00	4.38												

Table 6: Fama-MacBeth estimation, weekly holding returns, selected non-linearity controls, no moneyness dummies.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions. Squared Mkt, Hml and Umd are additional factors in first and second-stage regressions.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
	0.0448	0.0084	0.0372	0.0009	0.2044	0.0654	0.0012	-0.0017	0.0010			-0.0004	0.0006		0.1665	
	9.72	1.62	11.39	0.27	1.07	3.15	1.11	-1.21	0.88			-0.16	0.58		0.69	
(1)																
	0.0494	0.0493		0.1434		0.3951	0.4989									
	2.54	2.90		3.83												
	0.0500	0.0069	0.0379	0.0002	0.1831	0.0747	0.0010	-0.0019	0.0017							
	12.09	1.63	12.46	0.07	1.15	4.18	0.93	-1.51	1.57							
(2)																
				0.1234		0.3921	0.4767									
				4.28												
	0.0633	0.0075	0.0401	-0.0058	0.2568	0.0908						-0.0048	-0.0001		0.4193	
	13.61	1.80	13.17	-1.83	1.62	5.33						-3.40	-0.18		2.57	
(3)																
	0.0200	0.0295		0.0877		0.228	0.414									
	1.57	1.95		3.60												
	0.0454	0.0069	0.0414	0.0044	0.1643	0.0676	0.0017	-0.0009	0.0011	-0.0092	0.0016	-0.0001	-0.0006	0.0020	-0.0218	0.1220
	10.34	1.42	12.34	1.20	0.94	3.32	1.72	-0.60	0.94	-2.94	2.44	-0.02	-0.55	0.83	-0.10	0.37
(4)																
	0.0173	0.0496	-0.1447			0.3985	0.5195									
	1.00	2.77	-1.17													
	0.0440	0.0074	0.0404	0.0048	0.1494	0.0695	0.0011	-0.0019	0.0004	-0.0107	0.0011	-0.0014	-0.0008	0.0000	0.0378	-0.1015
	9.41	1.40	11.36	1.24	0.80	3.17	1.21	-1.30	0.32	-3.28	1.67	-0.56	-0.77	0.01	0.16	-0.29
(5)																
	0.0329	0.0416	-0.2198	0.1336		0.4015	0.5253									
	1.74	2.31	-1.75	3.87												

Table 7: Fama-MacBeth estimation, weekly holding returns, selected non-linearity controls, with moneyness dummies.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions. Squared Mkt, Hml and Umd are additional factors in first and second-stage regressions. Moneyness (categories 1 to 3) and put/call dummies are also included in second-stage regressions.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
(1)	0.0046	0.0057	0.0396	0.0339	0.1417	0.0224	0.0019	-0.0011	0.0005			-0.0031	-0.0016		0.0258	
	1.21	1.51	14.03	9.74	1.05	1.37	1.75	-0.94	0.50			-1.75	-2.09		0.15	
	0.0158	-0.0094		0.0561		0.3951	0.5117									
	1.09	-0.74		2.11												
(2)	0.0059	0.0059	0.0389	0.0321	0.1631	0.0221	0.0020	-0.0017	0.0011							
	1.74	1.73	14.68	9.99	1.29	1.50	1.88	-1.56	1.19							
				0.0514		0.3921	0.4767									
				2.36												
(3)	0.0093	0.0048	0.0412	0.0324	0.1944	0.0236						-0.0029	-0.0013		0.2498	
	2.61	1.30	13.42	8.77	1.40	1.55						-2.24	-2.14		1.75	
	-0.0092	-0.0106		0.0289		0.228	0.43									
	-0.81	-0.76		1.40												
(4)	0.0051	0.0049	0.0410	0.0329	0.0753	0.0162	0.0021	-0.0003	0.0003	-0.0006	0.0006	-0.0021	-0.0015	0.0004	-0.0127	-0.1380
	1.43	1.33	13.67	9.09	0.58	1.00	2.00	-0.27	0.32	-0.25	1.29	-1.22	-2.07	0.21	-0.08	-0.53
	0.0021	-0.0017	-0.0727			0.3985	0.5320									
	0.15	-0.13	-0.77													
(5)	0.0063	0.0049	0.0402	0.0322	0.0607	0.0202	0.0019	-0.0007	0.0000	-0.0014	0.0004	-0.0025	-0.0016	-0.0001	0.0278	-0.2389
	1.66	1.29	12.82	8.52	0.45	1.20	1.79	-0.61	-0.04	-0.60	0.93	-1.41	-2.07	-0.05	0.17	-0.89
	0.0059	-0.0044	-0.0924	0.0588		0.4015	0.5367									
	0.41	-0.32	-1.00	2.42												

Table 8: Fama-MacBeth estimation, weekly holding returns, with moneyness dummies and full set of non-linearity controls.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). *os* and *ss* are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the *EU* factor. *Mkt* and *Liq* are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. *Skew* and *Kurt* are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. *EU* is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions. Both first and second-stage regressions include squared factors. Moneyness (categories 1 to 3) and put/call dummies are also included in second-stage regressions.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
(1)	0.0048	0.0059	0.0422	0.0346	0.0914	0.0202	0.0019	-0.0010	0.0010			-0.0021	-0.0002		0.1615	
	1.27	1.54	14.01	9.57	0.70	1.27	1.80	-0.82	1.07			-1.19	-0.29		0.93	
	0.0026	-0.0054		0.0544		0.3969	0.5428									
	0.18	-0.43		2.02												
(2)	0.0066	0.0063	0.0392	0.0313	0.1519	0.0221	0.0020	-0.0020	0.0011							
	1.77	1.72	14.14	9.07	1.15	1.40	1.91	-1.73	1.11							
				0.0695		0.3945	0.4867									
				2.86												
(3)	0.0113	0.0048	0.0438	0.0336	0.0781	0.0292						-0.0034	0.0001		0.1891	
	2.81	1.25	12.81	8.06	0.52	1.80						-2.40	0.10		1.19	
	-0.0168	-0.0096		0.0398		0.2315	0.4763									
	-1.31	-0.72		1.71												
(4)	0.0067	0.0049	0.0436	0.0332	0.1179	0.0141	0.0024	0.0002	0.0004	0.0004	0.0007	-0.0013	-0.0012	0.0020	0.0414	-0.0753
	1.74	1.33	12.95	8.19	0.88	0.89	2.25	0.17	0.36	0.17	1.51	-0.72	-1.65	1.05	0.25	-0.31
	0.0086	-0.0089	-0.0981			0.4021	0.5842									
	0.63	-0.61	-0.94													
(5)	0.0077	0.0048	0.0438	0.0335	0.0924	0.0184	0.0021	-0.0003	0.0003	-0.0005	0.0005	-0.0018	-0.0011	0.0025	0.1180	-0.0418
	1.92	1.27	12.34	7.92	0.69	1.12	2.11	-0.25	0.24	-0.22	1.10	-0.92	-1.32	1.17	0.69	-0.15
	0.0022	-0.0119	-0.1058	0.0515		0.4054	0.5931									
	0.16	-0.77	-1.03	1.94												

Table 9: Fama-MacBeth estimation, weekly holding returns, selected non-linearity controls and moneyness dummies. Cyclical/non-cyclical stocks.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions. Squared Mkt, Hml and Umd are additional factors in first and second-stage regressions. Moneyness (categories 1 to 3) and put/call dummies are also included in second-stage regressions. Panels (1) and (2) - The macroeconomic uncertainty factor is built using *cyclical* and *non-cyclical* stocks, respectively, as defined in Section 5.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
	0.0031	0.0054	0.0490	0.0426	0.0821	0.0277	0.0036	-0.0001	-0.0002			-0.0024	0.0002		0.3137	
	0.71	1.14	12.43	8.65	0.72	1.34	3.22	-0.10	-0.11			-1.24	0.27		1.70	
(1)																
	-0.0153	-0.0136		0.0538		0.4133	0.5487									
	-0.95	-0.84		2.22												
	0.0052	0.0058	0.0398	0.0326	0.1425	0.0178	0.0025	-0.0012	0.0011			-0.0037	-0.0014		0.0660	
	1.42	1.66	14.68	9.96	1.05	1.20	2.24	-1.10	1.16			-2.06	-1.77		0.39	
(2)																
	0.0016	-0.0077		0.0306		0.4047	0.5190									
	0.12	-0.59		1.94												

Table 10: Fama-MacBeth estimation, weekly holding returns, selected non-linearity controls. Weighted Least Squares, and subperiod analysis.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions. Squared Mkt, Hml and Umd are additional factors in first and second-stage regressions.
Panel (1) - Results are based on Weighted Least Squares for second stage regressions. The Breusch-Pagan test shows heteroskedasticity related to the relative option spread os. Observations are assigned a weight equal to the inverse of the fitted value squared, calculated with respect to os. Panel (2) - as (1), over 1996-2001. Panel (3) - as (1), over 2002-2007, when Economic Derivatives were marketed.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix$_v$	Vix$_s$	Skew	Kurt
	Put	Put$_v$	Put$_s$	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
	0.0361	-0.0039	0.0403	0.0027	0.0415	-0.0201	0.0019	-0.0025	0.0002			0.0014	0.0003		0.1781	
	4.76	-0.53	6.97	0.36	0.14	-0.59	1.35	-1.43	0.09			0.38	0.13		0.42	
(1)																
	0.0054	0.0511		0.0893		0.4064	0.8322									
	0.17	1.62		2.80												
	0.0682	-0.0049	0.0564	-0.0003	0.7830	0.0289	0.0014	-0.0005	0.0017			-0.0093	-0.0019		-0.4320	
	5.25	-0.33	4.56	-0.02	1.31	0.51	0.70	-0.17	0.62			-2.86	-0.92		-1.14	
(2)																
	0.0124	0.0204		0.1426		0.3348	0.8024									
	0.33	0.61		2.33												
	0.0313	-0.0062	0.0377	0.0001	0.3849	-0.0265	0.0026	-0.0018	-0.0012			-0.0060	0.0004		0.1508	
	5.49	-0.94	7.07	0.01	1.44	-0.88	2.01	-1.09	-0.98			-2.25	0.30		0.42	
(3)																
	-0.0185	0.0298		0.0603		0.4798	0.8205									
	-0.86	1.29		2.48												

Table 11: Fama-MacBeth estimation, weekly average of daily hedged returns.

The table shows second-stage coefficients ($\hat{\lambda}s$) and t-stats. Standard errors are adjusted according to Shanken and Newey-West (4 lags). os and ss are the median relative option and stock bid-ask spreads. ν and γ are the median log vega and log gamma. β_s is the median stock beta with respect to the EU factor. Mkt and Liq are the market and liquidity factors. Vix, Vix_v, Vix_s are weekly changes in VIX, and changes in the weekly volatility and skewness of daily VIX changes. $Skew$ and $Kurt$ are changes in the weekly skewness and kurtosis of Dow Jones Industrial intradaily returns. Put, Put_v and Put_s are the weekly average of daily returns on out-of-the-money S&P 500 put options and changes in the weekly volatility and skewness of daily returns on out-of-the-money S&P 500 put options. EU is the macroeconomic uncertainty factor. $\bar{R}_1^2$ and $\bar{R}_1^2$ are the average adjusted R-squared from first and second-stage regressions.

	os	ss	ν	γ	β_s	Cons	Mkt	Smb	Hml	Umd	Liq	Vix	Vix_v	Vix_s	Skew	Kurt
	Put	Put_v	Put_s	EU		$\bar{R}_1^2$	$\bar{R}_2^2$									
(1)	-0.0008	0.0017	0.0042	0.0047	0.0122	0.0172	0.0024	0.0058	-0.0062			-0.0262	-0.0096		-0.3510	
	-1.10	2.16	5.54	6.15	0.45	4.74	0.41	1.48	-1.78			-5.73	-8.60		-1.19	
	-0.0704	-0.0695		0.1625		0.043	0.129									
	-1.72	-3.05		2.79												
(2)	-0.0029	0.0020	0.0033	0.0044	0.0177	0.0102	0.0128	0.0080	-0.0123							
	-6.57	4.62	8.49	11.38	1.36	5.32	3.74	3.36	-5.44							
				0.1677		0.029	0.082									
				5.03												
(3)	-0.0011	0.0016	0.0043	0.0049	0.0106	0.0168						-0.0305	-0.0096		-0.1135	
	-1.66	2.25	6.27	6.98	0.45	5.15						-6.73	-8.28		-0.40	
	-0.0803	-0.0718		0.1653		0.033	0.105									
	-2.23	-3.74		3.14												
(4)	-0.0012	0.0015	0.0041	0.0048	0.0217	0.0152	-0.0025	0.0018	-0.0050	-0.0152	0.0026	-0.0203	-0.0099	-0.0006	-0.4617	-0.9240
	-1.46	1.80	5.27	5.57	0.71	3.87	-0.40	0.49	-1.18	-3.67	2.59	-4.37	-7.64	-0.18	-1.41	-1.52
	-0.0588	-0.0880	0.5559			0.045	0.159									
	-1.38	-4.03	2.87													
(5)	-0.0011	0.0018	0.0042	0.0049	0.0218	0.0165	-0.0017	0.0011	-0.0051	-0.0131	0.0025	-0.0229	-0.0091	-0.0025	-0.2044	-0.3501
	-1.40	2.07	5.28	5.61	0.72	4.21	-0.27	0.29	-1.30	-3.22	2.58	-5.07	-7.30	-0.80	-0.64	-0.59
	-0.0575	-0.0798	0.4946	0.1436		0.046	0.163									
	-1.34	-3.74	2.53	2.30												

Table 12: Percentage of portfolios in which the best fitting polynomial time-series regression includes a squared term for the selected factor.

Among polynomial regressions with powers 1 and 2, the best fitting time-series regression is determined as the one with the lowest $D = n(1 + ln\frac{2\pi RSS}{n})$, where n is the number of observations and RSS the residual sum of squares. The table reports the percentage of portfolios in which the best-fitting regression includes a squared term for the selected factor.

Factor	**Hold.Ret.**	**Hedg.Ret.**
Mkt	25.51	2.15
Smb	1.02	3.86
Hml	7.14	0.86
Umd	5.61	0.86
Liq	3.57	2.15
Vix	1.53	0.00
Vix_v	0.51	0.00
Vix_s	1.53	1.29
Skew	0.00	0.86
Kurt	0.51	0.86
Put	0.00	0.86
Put_v	0.51	0.86
Put_s	0.00	0.00
EU	0.00	0.43

Table 13: Market risk premium estimated on simulated option returns, 1,000 replications.

Fama-MacBeth estimated market risk premium, and second stage intercept. Confidence intervals are based on bootstrapped standard errors. Option returns are winsorized at 0.175% and option portfolio returns at 0.35%. 1,000 replications. The 95% confidence interval for $\hat{\lambda}_{mkt}$ when Rp=0 includes 0.

Rp		**Average**	**90% C.I.**	
0.10	$\hat{\alpha}_2$	-.0003748	-.0024221	.0016726
	$\hat{\lambda}_{mkt}$	.0976612	.0944565	.1008659
0.00	$\hat{\alpha}_2$	.0005656	-.0015481	.0026793
	$\hat{\lambda}_{mkt}$	-.0036066	-.0067519	-.0004612