Idiosyncratic volatility related to behavioural phenomena in option returns

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Thijs Eerhard

479685

Supervisor: Dr. S. Vogel

Second assessor: XXX

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Abstract

This paper analyses the cross-section of stock option returns by sorting stocks on idiosyncratic volatility (ISV) on the one hand and the difference between historical volatility (HV) and implied volatility (IV) on the other hand and establishes a significant, positive difference in return between high and low ISV stocks. A zero-cost straddle and delta-hedged call trading strategy that is long in the portfolio with stocks with the largest, positive difference between HV and IV and the highest ISV and short the portfolio with the largest, negative difference and the highest ISV produces statistically and economically significant average, monthly returns. These results are robust to known risk-factor models, stock risk-factors and model assumptions, but are substantially impacted by high transaction costs.

Keywords: Idiosyncratic volatility, implied volatility, historical volatility, double-sorted portfolios, behavioural

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1 Introduction

There exists an interesting disparity in the relationship between the academic world and the stock market and the equity options market. Even though by some accounts the notational value of the global option market is actually larger than the global stock market, it receives far less attention. Cao and Han (2013) suggest this is the result of the view that options are merely leveraged positions in the underlying stocks. An equity option allows an investor to either buy or sell a stock against a pre-determined price. The value of the option essentially functions as a double-edged sword: it is determined by the price and volatility of the underlying stock, giving an investor the opportunity to trade on a view about the future price or volatility of the stock, but with a known option and stock price it also allows one to derive the expected future volatility. The most prevalent estimate of future volatility is implied volatility (IV), which can be obtained by inverting the Black-Scholes model.

If the future volatility is estimated incorrectly by investors, this will have the inevitable result that associated options are priced incorrectly. One interesting observation in that light by Andersen, Bollerslev, Christoffersen, and Diebold (2006) is the association of mean-reversion and expected future volatility. This means that over time, the IV will in most instances revert to the historical volatility (HV) of a stock, leaving room for investors to derive positive return by selectively buying and selling stocks with the largest difference between the HV and IV.

This investment strategy was implemented by Goyal and Saretto (2009) by sorting stocks into equally-weighted portfolios, that are rebalanced monthly on the basis of the log difference between HV and IV. The authors find that a zero-cost trading strategy of straddles, consisting of a long position in a portfolio of options with a large, positive difference between HV and IV and a short position in a portfolio of options with a large, negative difference, generates statistically significant returns of 22.7 percent per month.

These significant returns are consistent with investor overreaction, according to the authors. The deviations between HV and IV are very much transitory: the deviation is non-existent a year before or after the portfolio formation month and there is no traceable stock pattern, except in the formation month. This pattern of very large deviations between HV and IV associated with likewise stock return patterns indicates, according to the authors, that investors increase (decrease) their estimate of future volatility in excess of reality as a result of overreacting to current news events.

Such investor behaviour has earlier been established by Stein (1989), who found that investors overweight current short-term implied volatility in estimating long-term volatility. Goyal and Saretto (2009) apply this behavioural explanation to the cross-section of option returns and find that by using alternative, real-time estimates of implied volatility to estimate option prices and therefore option returns, the excess option returns completely disappear.

The potential return for an investor trading on this strategy is essentially a function of two parameters: the extent of the deviation between HV and IV and the reversal speed of IV. A larger deviation implies a larger reversal and a higher reversal speed will increase the return per time unit. The return can thus be improved in two ways. One could maximize the deviation between HV and IV by locating the portfolio initiation date at the exact time the deviation reaches it maximum. There are two difficulties involved with this strategy: the date where the deviation is maximized is different for each option and will increase the complexity of the trading strategy beyond fathomable levels. Even more so, how would one actually determine when the deviation is maximized? The other option is to increase the reversal speed, which is the focus of this paper.

What factor determines the reversal speed? The speed with which IV reverses will be determined by the ease that investors can rationally analyse and realize that their most recent estimation does not match the current state of affairs. Crucial in this process is the flow of information. As Hwang and Rubesam (2013) note: if public signals are noisy, they do not provide new information to the investor. The result is that the investor will not update their prior distribution and will rely on prior beliefs that are in line with the initial over(under)reaction. Therefore, the reversal speed will be determined by the extent that investors can access information of high quality associated with the company, ergo, by how noisy the information flow is.

A widely used proxy for the noise term in public signals is idiosyncratic volatility (ISV). A very important paper in that regard has been written by Cao and Han (2016). The authors concluded, albeit it for a different reason, that there is a significant, negative relationship between delta-hedged option returns and ISV in an OLS regression, with delta-hedged option returns as the dependent variable and ISV as the independent variable. Even more important, they found that this relationship strengthened after controlling for the deviation between HV and IV in the regression. This is a relevant indicator of the potential co-strenghtening relationship between the difference between HV and IV and ISV, but it is not more than a starting point to actually analyse ISV in the light of reversal speed.

The reasoning is thus as follows: to maximize returns, the mean reversion speed has to be maximized. On the basis of Hwang and Rubesam (2013), it is concluded that to maximize mean reversion speed, the noise in the information flow should be minimized. ISV is a proxy for noise and should therefore be minimized. Cao and Han (2016) not only confirm this expectation of a negative relation between option returns and ISV, but specifically validate the potential of combining the informational power of the difference between HV and IV and ISV.

This theoretical background derives certain expectations: (1). A positive relation between option returns and the mean reversion parameter. (2) A negative relation between option returns and ISV. (3). Combining the informational power of the difference between HV and IV and ISV in a trading strategy increases the option returns over solely using the difference between HV and IV.

With these expectations in mind, the main hypothesis of this paper is *that a double sort of stocks on the difference between HV and IV and ISV of the underlying stock significantly and positively increases the portfolio return over a single sort on the difference between HV and IV, robust to known risk-factor models, stock risk-factors, model specifications and transaction costs.*

To answer to the hypothesis of this paper, three steps are set out: (1). Establish the returns of a trading strategy consisting of a single sort on the difference between HV and IV in the context of a modern option dataset. (2). Establish that the returns of a trading strategy consisting of a double sort of stocks on the difference between HV and IV and ISV of the underlying stock significantly and positively increases the portfolio return over a single sort on the difference between HV and IV; this essentially constitutes proving expectation 3. To do that, the informational value of ISV and the mean reversion parameter first has to be proven. Expectation 1 will be proven by forming a mean reversion parameter and relating it directly to the double-sorted option returns in a regression. Expectation 2 will be proven by relating ISV to the full sample of option returns. (3). Control the results for known risk-factor models, stock risk-factors, model specifications and transaction costs.

This paper finds that the hypothesis of Goyal and Saretto (2009) extends to the present day (albeit with a smaller magnitude of 9.6 percent monthly straddle return) and more importantly, that it is outperformed by a zero-cost trading strategy involving a long position in the option portfolio with stocks with a high ISV and a large, positive difference between HV and IV and a short position in the option portfolio with stocks with a high ISV and a small, negative difference between HV and IV, displaying a monthly straddle return of 15 percent, thereby confirming expectation 3. At the basis of this observation is the finding that there is a significant difference in long-short option returns between high and low ISV stocks, which explains the decision to solely invest in high ISV stocks. In addition, expectation 1 is confirmed by directly regressing the mean reversion parameter on the double-sorted portfolio returns on a monthly basis and establishing a significant, positive relation between mean reversion and option returns.

The next step is to relate the option returns to aggregate risk factors (Q5-factor model) and stock risk-factors. Only the market factor under two specific circumstances displays significance in explaining the abnormal, double-sorted portfolio returns and all other factors relate in no way significantly to the abnormal returns. Even more so, the abnormal returns are very close to the raw returns, with thus almost no part of it relating to aggregate risk captured by the Q5-factor model. With respect to the stock risk-factors, a cross-sectional regression using the full sample is applied, with the straddle and delta-hedged call returns as the dependent variable and HV-IV, ISV and six other stock variables as the independent variables. All alpha's but one are insignificant, indicating that almost all variation in the option returns can be captured by the combination of HV-IV and ISV and certain stock variables. HV-IV and ISV are significant in each regression with varying variables. This also indicates that ISV is a relevant addition to HV-IV in explaining option returns and more importantly, the significant, negative relation between the option returns and ISV confirms expectation 2.

Observing a significant, negative relation between the option returns and ISV, while still only investing in high ISV stocks might seem contradictory, but this would only be true with a portfolio that is solely long into low ISV stocks. With a long-short portfolio, the interaction with HV-IV creates an asymmetric effect that has caused it to be more profitable to invest in high ISV stocks, regardless of the higher return of low ISV stocks, because with a long-short portfolio, one can profit from extreme underperformance of high ISV stocks with a negative difference between HV and IV.

In line with academic literature and Goyal and Saretto (2009), transaction costs significantly reduce the profitability of the trading strategy. Assuming an effective spread to quoted spread of 50 percent is sufficient to reduce returns to zero for both types of returns. Including stock trading costs, 25 percent is sufficient in regard to the straddle return and with delta-hedged calls, trading at the midpoint ceases to be profitable. This shows that transaction costs might evaporate any possible returns of a double-sorted portfolio strategy, especially if the effective spread is large (close to 50 percent). Depending on the expected level of transaction costs, the strategy might or might not be statistically and economically significant. What is still interesting is that the difference in return between high and low ISV is maintained, even if the trading costs increase.

The double-sorted portfolio returns are robust to weighting method, moneyness range and time period chosen. The decision to either use equal-weighting or value-weighting does have impact on both the straddle and delta-hedged call returns, reducing the mean return from a monthly 15 percent and 1.6 percent respectively to 8.5 and 0.9 percent. One can also observe that the extreme values become more extreme. Nevertheless, the straddle returns are still significant at 1 percent and the delta-hedged call returns still significant at 5 percent.

Changing the moneyness range from being between 0.95 and 1.05 to 0.9 and 1.1 has barely any effect on the actual raw returns, despite a minor increase, certainly not significantly. Lastly, the sample period is split into two subsamples, before and after 2006, therefore equal to the period studied by Goyal and Saretto (2009) and all years that they have not studied in their paper. The clear observation is that after 2006 the double-sorted portfolio returns are lower for both types of returns, with more extreme values and a lower Sharpe Ratio. Nevertheless, both types of returns remain significant at 1 percent. This pattern, a substantial decrease in return, is not only observed for the double-sorted portfolio returns, but also for the single-sorted returns on HV-IV.

With this paper, the author adds to the existing literature by displaying that the observation by Goyal and Saretto (2009) that a zero-cost trading strategy on the difference between HV and IV produces significant returns, still holds true to this day, with a dataset that is more than five times larger. What is truly unique about this paper is that it is shown that their strategy can be significantly improved upon, controlling for known risk-factor models and stock risk-factors, by adding the element of ISV, theoretically and empirically founded by the new-found idea of increasing the reversal speed in a behavioural context. The indirect link established between the mean reversion parameter and portfolio returns through ISV is not only promising in regard to mean reversion in option volatility, but might have potential for application in other fields of research within economics. It also contributes to the debate about the existence of efficient markets, by improving on a trading strategy that very likely exploits a behavioural bias, producing significant, abnormal returns that are not consistent with the existence of efficiency in markets.

Furthermore, the results confirm the prior found relationship between option returns and ISV of the underlying stock by Cao and Han (2016) and also relate to the recently growing literature revolving around researching the relationship between(delta-hedged) option returns and stock characteristics by Cao et al (2021) and Gao et al (2018), increasingly showing the existence of possible anomalies in the field of options that provide opportunities for abnormal returns.

The results also have relevance for practitioners in the field of option trading. With Goyal and Saretto (2009), a singular way was already established to produce significant returns. With this paper, not only can practicioners learn that the initial strategy still holds true to this day, even more important, a new strategy is set out in which option returns can be significantly increased. Furthermore, the paper also functions as a mirror to the behavioural traits of traders, which might have created the regularity discussed in this paper.

The rest of the paper is organized in the following way: in Section 2 the datasets collected from Optionmetrics, CRSP and Compustat and how they were filtered is discussed. In Section 3, the HV-IV hypothesis in a modern context is discussed, along with proving the informational value of ISV and the mean reversion parameter and discussing the double-sorted portfolio returns. Lastly, Section 4 discusses the extent to which the results are robust to known aggregate risk factors, stock risk-factors, transaction costs and the assumptions underlying this paper.

2 Data

The data that is the subject of this paper has three sources: the OptionMetrics Ivy DB Database, CRSP and Compustat. OptionMetrics is used to gather daily closing bid and ask quotes for American equity options, in addition to the IV, delta, gamma and vega, open interest and the strike price for the period of the 4th of January 1996 to December 31st 2020.

Multiple data filters are applied to minimize the potential impact of recording errors. Any observation with a bid price equal to or lower than zero is eliminated; this is also true for observations where the ask price is lower than the bid price. All observations for which the bid-ask spread is lower than the minimum tick size (equal to $0.05 for option trading below $3 and $0.10 in any other case) also get eliminated. In line with Driessen, Maenhout, and Vilkov (2009), all observations for which the option open interest is equal to zero are also eliminated, in order to eliminate options with no liquidity. Lastly, all observations that violate arbitrage bounds are removed, in accordance with equation 2.1 for call options and 2.2 for put options:

$$Price < Option\ Cost\ at\ Midpoint < Max(0, Price - Strike * e^{-Rf*(1/252))}) \tag{2.1}$$

$$Strike < Option\ Cost\ at\ Midpoint < Max(0, Strike * e^{-Rf*(1/252))} - Price) \tag{2.2}$$

The filtered OptionMetrics dataset is used to develop portfolios based on information available on the first trading day, which is usually a Monday, directly following the expiration Saturday of the same month (all options expire on the Saturday immediately following the third Friday of the expiration month). In the instance that the particular Monday is a non-trading day, the first trading day within four days later than the Monday is taken instead. If none of the days in that particular week are trading days, the option data is eliminated. With the goal of establishing a continuous time-series with constant maturity, only options that have a time to maturity of one month left are considered.

To ensure that only the most liquid options contracts are part of the final dataset, only options with a ratio of strike to stock price (moneyness) between 0.95 and 1.05 are considered. In particular, such a narrow range is chosen because of two reasons: with a narrow range, the option returns are not determined by the smile in the volatility surface. The second reason is related to the type of strategy employed in this paper, a strategy aimed at exploiting volatility. To maximize the effectiveness of this strategy, options should be chosen with a high sensitivity to volatility changes, measured by vega. Vega is the highest close to ATM and therefore, to maximize the potential of the volatility strategy, only options that are very close to ATM should be considered.

The final dataset consists of one put and one call contract per firm in each month with moneyness close to 1. These contracts will be held for one month, until expiration, after which the process starts again. The final dataset consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks. Each of the monthly pairs has non-missing observations on the data that is required to calculate the straddle and delta-hedged call returns.

The Compustat database is used to gather data for two stock risk-factors that are used as control factors, respectively size and book-to-market value (BM). Regarding the Compustat data, firms which have less than two years of data are removed to avoid a back-filing bias, in accordance with Loughan and Wellman (2011) and firms with a negative book value of equity are also removed, based on Fama and French (1993). Following Fama and French (1993), size is equal to the market value of equity and is defined as the share price multiplied with the amount of shares outstanding (CRSP items PRC and SHROUT). BM is defined as the book equity divided by size, with book equity equal to equity value plus deferred taxes and investment tax credit minus preferred stock value. The latter, depending on availability and analogous to Fama and French (1993), is equal to the redemption- (Compustat item PSTKRV), liquidation- (item PSTKL), or par-value (item PSTK), in that order. Equity value is defined as, depending on availability, stockholders's equity (Compustat item SEQ), ordinary shares equity plus preferred stock at redemption value (items CEQ and PSTKRV), total assets minus liabilities (items AT and LT) or simply book values per shares times shares outstanding (items BKVLPS and CSHO), in that order. The Compustat data is coupled with the CRSP data by merging the daily price information from the CRSP data set from July in year t to June in year t +1 with the Compustat data of year t-1.

Table 2.1: Summary Statistics.

HV is defined as the standard deviation of the daily stock return of the past 252 trading days. The calculation of ISV consists of two steps: (1). The daily return over all observations is regressed on the daily market return over the past 252 trading days, (with a minimum of 21 trading days required) which determines the residual return. (2). ISV is defined as the standard deviation of the residual return of the past 252 trading days. ISV and HV are annualized by multiplying the value by the square of 252, for the amount of trading days in 1 year. IV is calculated as the average of the implied volatility of the monthly put and call contract. Delta represents the difference between this month and the previous month, calculated by each stock. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Mean	**Std. Dev.**	**Min**	**Med**	**Max**	**Kurt**	**Skew**
HV	.525	.289	.017	.464	7.068	47.895	3.620
IV	.517	.254	.021	.464	2.637	6.692	1.430
ISV	.468	.286	.009	.411	7.028	50.341	3.665
ΔHV	.004	.058	-.964	.001	1.676	152.262	3.485
ΔIV	-.002	.067	-.886	-.000	0.916	43.202	0.084
ΔISV	.003	.053	-.970	.001	1.674	198.704	4.795

For each stock and for each month in the sample, three different measures of volatility are calculated: historical volatility (HV), implied volatility (IV) and idiosyncratic volatility (ISV). The CRSP dataset consisting of the daily price data is the basis of the HV, ISV and the stock trading costs (discussed in Section 4) calculations. HV is defined as the standard deviation of the daily stock return of the past 252 trading days. The calculation of ISV consists of two steps: (1). The daily return over all observations is regressed on the daily market return over the past 252 trading days, (with a minimum of 21 trading days required) which determines the residual return. (2). ISV is defined as the standard deviation of the residual return of the past 252 trading days. ISV and HV are annualized by multiplying the value by the square of 252, for the amount of trading days in 1 year.

IV is calculated as the average of the implied volatility of the monthly put and call contract from the OptionMetrics database. The average of each stock per month is calculated, thereby creating a time-series for each stock. The cross-sectional average of IV, HV and ISV is reported regarding all relevant statistics (median, standard deviation, minimum, maximum, skewness, and kurtosis) in Table 2.1, essentially mimicking the summary statistics of an individual stock. The mean value of HV and IV is extremely close, respectively with a value of 52.5 percent and 51.7 percent; in addition, HV is slightly larger than IV, in line with Goyal and Saretto (2009) and Driessen, Maenhout, and Vilkov (2009). HV is more positively skewed and more variable than IV and also displays a larger kurtosis, in contrast with Goyal and Saretto (2009), most likely resulting from using a larger and more recent dataset. This gives a first indication that the fundamentals may have changed since Goyal and Saretto published their findings. ISV is smaller than both HV and IV at 46.8 percent and, as expected, has a distribution that is very similar to HV in terms of variance, skewness and kurtosis. One can deduce that most of the volatility in stock returns is idiosyncratic, thus specific to each stock.

In addition to this, a time series has been created of the monthly change in HV, IV and ISV. The monthly change in either HV, IV or ISV is close to zero on average, but has large spikes over time relating to important information disclosures relevant to a specific stock, visible in the relatively high variance. For example, the largest negative spike in HV is minus 96.4 percent in one month.

3 Results

In the introduction, it was set out that to answer to the hypothesis of this paper, the research is designed around three vital steps. The subsection *HV-IV* will cover step 1: establish the returns of a trading strategy consisting of a single sort on the difference between HV and IV in the context of a modern option dataset. This involves replicating the research design of Goyal and Saretto (2009), while using a dataset that is five times larger, to extend their work to modern times and develop a baseline for the introduction of ISV. In the subsection *Idiosyncratic Volatility* step 2 will be covered.

3.1 HV-IV

3.1.1 Portfolio Formation

The construction of the modern-day extension of the Goyal and Saretto (2009) research design starts with the portfolio construction process. This process essentially revolves around two types of portfolios. The first type of portfolio is constructed by sorting each stock into a decile in accordance with the log difference between HV and IV respectively. Portfolio 1 holds the stocks with the most negative or lowest, negative difference between HV and IV and portfolio 10 will hold the stocks with the largest or largest positive difference. Each decile is equal-weighted and rebalanced on a monthly basis. The second type of portfolio consists of two deciles, positive (P, HV higher than IV) and negative (N, HV smaller than IV). These two portfolios are monthly rebalanced and relative value-weighted, weights in each of the two groups are proportional to the (absolute) deviation between HV and IV.

Table 3.1 on the next page displays the descriptive statistics of both types of portfolios. The average is calculated over each stock per month, resulting in a continuous time-series, either equally-weighted or value-weighted in line with the respective weighting method. The statistics displayed in the table are the time-series average of these statistics.

Table 3.1: Formation period statistics of all portfolios, sorted on the difference between HV and IV.

The decile portfolios are constructed by sorting each stock into a decile in accordance with the log difference between HV and IV. Portfolio 1 holds the stocks with the most negative or lowest negative difference between HV and IV and portfolio 10 will hold the stocks with the largest or largest positive difference. Each decile is equal-weighted and monthly rebalanced. The last two portfolios, positive (P, HV higher than IV) and negative (N, HV smaller than IV), are relative value-weighted, weights in each of the two groups are proportional to the (absolute) deviation between HV and IV. The average is calculated over each stock per month. The sample consist of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Decile portfolios											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(N)	(P)
$HV_t - IV_t$	-.189	-.082	-.046	-.022	-.002	.015	.035	.057	.088	.191	-.109	.116
HV_t	.430	.441	.448	.460	.464	.470	.482	.498	.522	.603	.457	.566
IV_t	.618	.523	.494	.482	.466	.455	.448	.442	.434	.412	.567	.450
Δ^c	.548	.541	.537	.534	.530	.525	.522	.519	.515	.514	.539	.524
Δ^p	-.457	-.466	-.469	-.472	-.477	-.482	-.485	-.489	-.493	-.496	-.468	-.484
Γ	.178	.174	.173	.172	.175	.174	.175	.177	.183	.209	.183	.203
ν	3.326	3.613	3.709	3.726	3.794	3.808	3.821	3.835	3.795	3.686	3.289	3.495

Observing Table 3.1, there is a clear pattern in both HV and IV in analysing the deciles from 1 to 10: HV increases, whereas IV decreases. Because of this opposing movement, the difference between HV moves from negative 18.9 percent at decile 1, close to zero at decile 5, until positive 19.1 percent at decile 10. The spread between decile 1 and 10 for HV (17.3 percent) and IV (20.6 percent) is relatively dissimilar and larger for IV, displaying that a sort on the difference between HV and IV is more than merely exploiting different levels of IV, but captures a certain dynamic of that difference. With the P and N deciles, the exact same pattern is observed, although the pattern is less extreme than by strictly looking at decile 1 and 10, implying that the extreme decile portfolios contain options with more severe deviations of HV and IV than the P and N portfolios.

The option Greeks, delta, gamma and vega, do not appear to display a pattern and do not vary much in analysing the deciles from 1 to 10. The only observation that could be made is a slight, opposing pattern in the delta of the call and the delta of the put options. This pattern was also observed with Goyal and Saretto (2009) and absolute values of the option Greeks are extremely similar as well. This is also true for the P and N portfolios.

3.1.2 Portfolio Returns

A simple, but important decision in developing and implementing a research design revolves around the calculation of the option returns. The goal is to solely study the volatility characteristics of the options and not report any irrelevant or unwanted movements which provides no information in regard to the hypothesis. Therefore, it is necessary to neutralize movements in the underlying stock. To achieve this goal, the decision was made to work with two types of returns: straddle returns and delta-hedged call returns. Delta-hedged put returns are similar to delta-hedged call returns and are therefore not discussed. A straddle return is the return of a straddle portfolio, which is the combination of a call and put option on the same stock, with equal strike price and maturity. A delta-hedged call return is the return of a delta-hedged call portfolio, consisting of a call option plus delta shares of the underlying stock sold short at the initiation date and an equal amount of shares of the underlying stock bought at expiration.

There are two important things to note: the delta-hedged call portfolios are not rebalanced, as is commonly applied, during the period until expiration that they are held. This decision, made out of simplicity concerns, has a two-fold effect: on the one hand, it saves this strategy from incurring high transaction costs because of frequent rebalancing to trade the underlying stock, needed to adjust the delta to the desired level; on the other hand, because the delta will change over the period the portfolio is held, movements in the underlying stock will not be completely neutralized as a result, increasing the risk of the strategy. Secondly, this paper uses data on American options. One important characteristic of American options is the possibility of early exercise. This possibility is ignored because of simplicity concerns and the net effect on the returns is not clear, as suggested by Poteshman and Serbin (2003).

For each stock and for each month in the sample, a call and put contract with the same underlying stock, maturity and strike price are matched, that is also approximately ATM and has one month to maturity. The next step is to construct a time-series of straddle and delta-hedged call returns. Equation 3.1 displays the calculation of straddle returns for call options, equation 3.2 for put options and equation 3.3 shows the calculation of delta-hedged call returns:

$$\begin{aligned} Straddle_c = (&Max(0, Expiration\ Price - Strike)/ \\ &Sum\ of\ Put\ and\ Call\ Option\ Cost) - 1 \end{aligned} \tag{3.1}$$

$$\begin{aligned} Straddle_p = (&Max(0, Strike - Expiration\ Price)/ \\ &Sum\ of\ Put\ and\ Call\ Option\ Cost) - 1 \end{aligned} \tag{3.2}$$

$$\begin{aligned} Hedge_c = ((&Max(0, Expiration\ Price - Strike) + Trading\ Delta * Price \\ &- Call\ Option\ Cost - Trading\ Delta * Expiration\ Price)/ \\ &(Call\ Option\ Cost + Trading\ Delta * Expiration\ Price) \end{aligned} \tag{3.3}$$

To highlight the meaning of the prior equations, the calculation of the straddle portfolio returns consist of two elements: the profit and the cost. The profit is equal to the terminal payoff of the option that expires in the money, which depends on the stock price at expiration and the strike price of the option. The cost is equal to the sum of the average of the closing bid and ask quotes of the call and put. Dividing the profit by the cost and subtracting 1 delivers the straddle return.

The calculation of the delta-hedged call portfolio returns consists of the same elements. The profit is equal to the sum of the terminal payoff and the delta on the first trading date times the trading price on that day, minus the cost of the delta-hedged call portfolio. The cost of the delta-hedged call portfolio is equal to the average of the closing bid and ask quote of the call option plus the amount of shares bought at the first trading date of the portfolio multiplied with the expiration price. The return is equal to the profit divided by the cost.

An important difference has to be made between the portfolio formation date and the first trading date. To avoid microstructure biases, there is a difference of one day implemented between the portfolio formation signal, the difference between HV and IV, and the day the portfolio is first traded. The signal is taken and the portfolio is formed on the first trading day after the expiration Friday of the month, usually a Monday. The portfolio is traded on the second trading day after the expiration Friday of the month. In the instance that the particular Tuesday is a non-trading day, the first trading day within four days later than the Tuesday is taken instead. If none of the days in that particular week are trading days, the option data is eliminated. A similar approach is applied in regard to the expiration date: in many instances, the OptionMetrics database lacks data on or close to the expiration date of an option. Therefore, if there is no price information on the closing date, the first available data in the six days prior is used. If at none of those days any information is available, the option is eliminated.

Table 3.2: Post-formation period returns of all portfolios, sorted on the difference between HV and IV.

The calculation of the straddle portfolio returns consist of two elements: the profit and the cost. The profit is equal to the terminal payoff of the option that expires in the money, which depends on the stock price at expiration and the strike price of the option. The cost is equal to the sum of the average of the closing bid and ask quotes of the call and put. Dividing the profit by the cost and subtracting 1 delivers the straddle return. The calculation of the delta-hedged call portfolio returns consists of the same elements. The profit is equal to the sum of the terminal payoff and the delta on the first trading date times the trading price on that day, minus the cost of the delta-hedged call portfolio. The cost of the delta-hedged call portfolio is equal to the average of the closing bid and ask quote of the call option plus the amount of shares bought at the first trading date of the portfolio multiplied with the expiration price. The return is equal to the profit divided by the cost. The returns are equal-weighted (for deciles) or value-weighted (for P and N portfolios) across all the stocks in the portfolio on a monthly basis. SR stands for Sharpe Ratio. SR is annualized. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Decile Portfolios													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10-1)	(N)	(P)	(P-N)
Panel A: Straddle Returns														
Mean	-.040	.016	.013	.027	.033	.033	.026	.030	.047	.056	.096	-.025	.027	.053
Std	.265	.310	.304	.322	.319	.345	.342	.338	.351	.322	.211	.254	.265	.188
Min	-.435	-.493	-.446	-.406	-.431	-.401	-.413	-.419	-.425	-.378	-.932	-.465	-.500	-.709
Max	2.904	3.400	3.288	3.489	3.324	3.607	3.887	3.538	3.587	2.877	1.224	2.553	1.964	.876
SR	-.523	.178	.144	.291	.356	.327	.266	.302	.466	.599	1.571	-.346	.357	.970
Panel B: Delta-Hedged Call Returns														
Mean	-.000	.003	.003	.004	.005	.005	.006	.006	.007	.008	.009	.002	.006	.004
Std	.036	.039	.038	.041	.039	.044	.040	.042	.041	.040	.021	.043	.037	.027
Min	-.058	-.058	-.050	-.052	-.052	-.044	-.053	-.044	-.047	-.041	-.065	-.064	-.060	-.184
Max	.395	.487	.468	.526	.455	.556	.489	.538	.489	.417	.113	.464	.323	.115
SR	-.039	.271	.303	.355	.465	.423	.491	.456	.599	.725	1.459	.156	.538	.486

Each option is designated to a certain portfolio. The average, monthly return is calculated for each portfolio to create a continuous time-series of option returns, either equally-weighted or value-weighted depending on the type of portfolio. Assuming that a long-short portfolio with zero wealth invested should have zero return, a long-short variable is constructed, equal to the difference between the average return on portfolio 10 and portfolio 1. Under this assumption, a t-test under null hypothesis equal to zero is applied, using Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors and a correction for twelve lags, as twelve lags is most appropriate for a dataset that spans several decades and has monthly data.

Table 3.2 displays the summary statistics of both the straddle and delta-hedged call portfolio returns in regard to both type of portfolios that have been described earlier: the 10 decile portfolios and the positive and negative portfolio. The statistics displayed in the table are the time-series average of these statistics. Any significant coefficient in this t-test will indicate that the hypothesis of Goyal and Saretto (2009) also applies to the period of 1996 until 2020. In addition to standard summary statistics, the Sharpe Ratio, a measure of the risk-return tradeoff, is displayed. The Sharpe Ratio is calculated as the average return divided by the monthly standard deviation and annualized by multiplying this number by the square of 12.

Panel A of Table 3.2 displays the relevant statistics of the straddle portfolios. The average return varies from –4.0 percent in decile 1, continuously increasing to 5.6 percent in decile 10, a difference of 9.6 percent. This is substantially lower than what Goyal and Saretto (2009) found. The accompanying standard deviation is relatively low and consistent across each decile, with no clear pattern. The long-short straddle portfolio (10-1) produces a significant at 1 percent (t-value of 5.68), 9.6 percent return per month. The Sharpe ratio of the straddle strategy is also very substantial, at 1.571. The P-N straddle portfolio has a substantially lower average return at 5.3 percent. The monthly return of 5.3 percent is significant at 1 percent (3.66), but is lower than the 10-1 portfolio, very likely because it does not exploit the most extreme deviations of HV and IV, as discussed in the data section. Likewise, the Sharpe Ratio is lower, at 0.97.

With the delta-hedged call returns in Panel B of Table 3.2, a very similar pattern is observed as compared to the straddle returns: returns increase from decile 1 to 10 and the standard deviation is constant and displays no pattern. What is different is the magnitude of the returns: the returns are very small and close to zero. This difference can be logically explained from two perspectives. (1). Straddles can exploit mispricing in both calls and puts, whereas delta-hedged calls can solely exploit the mispricing in calls. (2). A delta-hedged call portfolio partly consist of an investment in the underlying stock, passively neutralizing stock price movements. Also, regarding investments in the underlying stock, no mispricing is assumed. Regardless, a clear pattern in mean option returns is visible. The long-short portfolio produces a 0.9 percent return per month, significant at 1 percent (4.76), with a substantial Sharpe Ratio of 1.459, not dissimilar to the straddle returns, despite the difference in the magnitude of the returns. The P-N portfolio produces an even smaller, monthly return of 0.4 percent, significant at 10 percent (1.96), with a less impressive Sharpe Ratio of 0.486.

It must also be highlighted that the statistical significance of the monthly option returns, either straddle or delta-hedged call or more specifically, the spread in option returns across portfolios, is not the result of the reality that stocks in decile 1 have high IV and in decile 10 have low IV. A sort solely on HV or IV still displays a statistically significant difference in return between decile 10 and 1.

3.2 Idiosyncratic Volatility

In the introduction, it was set out that to answer to the hypothesis of this paper, the research is designed around three vital steps. In the subsection *Idiosyncratic Volatility* step 2 will be covered: establish that the returns of a trading strategy consisting of a double sort of stocks on the difference between HV and IV and ISV of the underlying stock significantly and positively increases the portfolio return over a single sort on the difference between HV and IV; this essentially constitutes proving expectation 3. Essentially, the goal is to prove there is a significant difference in option returns between high and low ISV and use that information to improve the option returns with a double-sort on the difference between HV and IV and ISV. To do that, the informational value of ISV and the mean reversion parameter first has to be proven. Expectation 1 will be proven by forming a mean reversion parameter and relating it to the double-sorted option returns. Expectation 2 will be proven by relating ISV directly to the full sample of option returns.

3.2.1 Informational Value

The addition of ISV should not only be theoretically founded, as was laid down in the introduction, but also empirically supported. In the words of John Locke, experience is the sole guide of the acquirement of knowledge and thus this envoyage to acquire knowledge should be guided by experience. Goyal and Saretto (2009) displayed that volatility is highly mean-reverting and therefore, that any forecast of future volatility must account for this. One of those forecasts is embedded in the IV of a stock. The hypothesis derived from this, is that IV captures some information about future volatility. The idea founding this paper is that ISV also captures some information about future volatility.

To motivate this proposition, a standard rationality test is constructed on the relation between future realized volatility (FV) and HV, IV and ISV, in line with Christensen and Prabhala (1998), applying two monthly cross-sectional regressions, as displayed in equation 3.4 and 3.5:

$$\mathrm{Fv}_{i,t+1} = \alpha_t + \beta_{1t}\mathrm{iv}_{i,t} + \beta_{2t}\mathrm{hv}_{i,t} + +\epsilon_{i,t+1} \tag{3.4}$$

$$\mathrm{Fv}_{i,t+1} = \alpha_t + \beta_{1t}\mathrm{iv}_{i,t} + \beta_{2t}\mathrm{hv}_{i,t} + \beta_{3t}\mathrm{isv}_{i,t} + \epsilon_{i,t+1} \tag{3.5}$$

In equation 3.5, which is equal to equation 3.4 extended with ISV, *fv* is the log value of FV over the total life of the option, defined as the standard deviation of daily returns. *Hv* and *iv* are the log value of HV and IV. There is one cross-section regression without ISV and one with ISV as explanatory variable, to compare the result of the addition of ISV and to prove that ISV captures certain information about FV that is not subsumed by HV and IV. The null hypothesis that underlies the regressions is that, if IV, HV and ISV do not contain significant information on FV, ergo, are an unbiased forecast of FV, the parameters α, β_1, β_2 and β_3 should have a value equal to, respectively, zero, one, zero and zero. The regressions are applied on a monthly basis to calculate the time-series average of the regression coefficients, using Newey West (1987) heteroskedasticity and autocorrelation consistent standard errors and a correction for twelve lags.

In the multivariate regression (equation 3.4) with only HV and IV as explanatory variables, it is observed that $\beta_1(\beta_2)$ is equal to .617 (.097), with t-values of 33.35 (15.97), which is relatively similar to Goyal and Saretto (2009). After adding ISV in the multivariate regression (equation 3.5) as explanatory variable, both β_1 and β_2 remain very significant with respective values of .478 and .093, whereas more importantly, β_3 is equal to 0.135 and significant at 1 percent, with a t-value of 3. This is an important indication that ISV adds new information with respect to FV that is not subsumed by HV and IV and that it is not an unbiased predictor of FV.

3.2.2 Mean Reversion Parameter

The mean reversion parameter is the result of an autoregressive model with 1 lag in an univariate framework, an AR(1) process. The variable that is assumed to be mean-reverting, is equal to the difference between HV and IV. In the framework of Goyal and Saretto (2009), that variable should mean-revert to zero in the long-run. The goal is to establish the mean-reverting level of each double-sorted portfolio individually, as to be able to compare different levels of the difference between HV and IV and ISV. The first part of the process is to average the difference between HV and IV for each firm on a daily basis over the multiple options each firm has available. Only stocks which have been designated to a certain double-sorted portfolio in the portfolio formation process are used. A monthly regression for each firm is applied in accordance with equation 3.6:

$$\mathrm{HV} - \mathrm{IV}_{i,t} = \alpha_t + \beta_1 \mathrm{HV} - \mathrm{IV}_{i,t-1} + \epsilon_{i,t} \tag{3.6}$$

After establishing β_1 on a monthly basis for each firm (requiring a minimum of 14 observations), it is then averaged across each portfolio on a monthly basis. β_1 is essentially what is most interesting, because it displays the extent to which prior values are correlated with current values of the difference between HV and IV. The closer this value is to 1, the stronger the mean reversion; the closer it is to 0, the weaker the mean reversion is. Within the behavioural framework that this paper has adopted, it is expected that there is a positive relationship between β_1 and the double-sorted portfolio returns. In the next subsection, the mean reversion parameter determined with the aforementioned method will be regressed directly on the double-sorted option returns to test expectation 1.

3.2.3 Double-Sorted Returns

The implementation of the addition of ISV in terms of portfolio formation follows a similar process as described before. This paper will now focus solely on decile portfolios and not on the P-N portfolios, because the focus will now shift to ISV and the deciles are more relevant with respect to researching ISV. A double-sort is implemented in a 5x10 system with dependent sorting (baseline is ISV), on the log difference between HV and IV and ISV, equally-weighted and monthly rebalanced. The returns are calculated in the same way as described before and the same procedures still apply.

As one will observe in Table 3.3 on the next page, the mean reversion parameter and statistics of double-sorted option returns are displayed of the high and low HV-IV and ISV portfolios and four specific double-sorted portfolios. Why these four specific portfolios? To reiterate again, the goal of this subsection is to display that there is a significant difference in option returns between high and low ISV stocks and use that information to generate a double-sorted portfolio that outperforms a single-sorted portfolio on the difference between HV and IV. To prove this, one has to compare a long-short portfolio solely invested in high ISV stocks and a long-short portfolio solely invested in low ISV stocks.

A t-test under null hypothesis equal to zero is applied, using Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors and a correction for twelve lags. If the difference between those two long-short portfolios is significant, ISV does matter with respect to option returns over the time period 1996 to 2020 and could be used to improve the option returns over a single-sort. That is why those four portfolios are especially relevant, which consist of: low ISV and a low, negative difference between HV and IV (1), low ISV and a high, positive difference between HV and IV (2), high ISV and a low, negative difference between HV and IV and (3) high ISV and a high, positive difference between HV and IV (4).

Table 3.3: Post-formation period returns and mean reversion parameter of relevant portfolios, sorted on the difference between HV and IV and ISV.

A double-sort is implemented in a 5x10 system with dependent sorting (baseline is ISV), on the log difference between HV and IV and ISV, equally-weighted and monthly rebalanced. The returns are calculated in a similar fashion as in Table 3.2. The mean reversion parameter is the result of an autoregressive model with 1 lag in a univariate framework, an AR(1) process. The variable that is assumed to be mean-reverting, is equal to the difference between HV and IV. The four portfolios consist of: low ISV and a low, negative difference between HV and IV (1), low ISV and a high, positive difference between HV and IV (2), high ISV and a low, negative difference between HV and IV and (3) high ISV and a high, positive difference between HV and IV (4). The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	HV-IV		**ISV**		**Double-Sorted**				
	(Low)	(High)	(Low)	(High)	(1)	(2)	(3)	(4)	(Difference)
Panel A: Straddle Returns									
Mean	-.043	.060	.040	.010	.016	.071	-.095	.055	.095***
Std	.248	.369	.450	.228	.543	.579	.227	.354	.613
Min	-.415	-.417	-.518	-.355	-.740	-.620	-.604	-.468	-1.287
Max	2.582	3.785	5.426	1.731	5.194	6.528	1.060	2.245	5.414
SR	-.606	.568	.311	.153	.103	.426	-1.454	.541	.539
Panel B: Delta-Hedged Call Returns									
Mean	-.000	.008	.005	.005	.005	.007	-.007	.009	.014***
Std	.037	.036	.034	.047	.046	.036	.050	.050	.062
Min	-.058	-.039	-.046	-.047	-.065	-.054	-.096	-.053	-.180
Max	.383	.409	.448	.508	.402	.404	.286	.406	.432
SR	-.034	.729	.473	.355	.405	.675	-.476	.612	.791
Panel C: Mean Reversion Parameter									
Mean	.684	.727	.751	.671	.737	.723	.601	.702	.115

*White (1980) Heteroskedastic consistent standard errors. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

Table 3.4: Post-formation period returns, comparing a single-sort on the difference between HV and IV with a double-sort on the difference between HV and IV and ISV.

The *Single* portfolio is constructed by taking the long-short portfolio of the single-sort on the difference between HV and IV. The *Optimized* portfolio is long in the portfolio with stocks with the largest, positive difference between HV and IV and the highest ISV and short the portfolio with the largest, negative difference and the highest ISV. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Decile Portfolios	
	Single	Optimized
Panel A: Straddle Returns		
Mean	.096***	.150***
Std	.211	.348
Min	-.932	-.863
Max	1.224	2.657
SR	1.571	1.497
Panel B: Delta-Hedged Call Returns		
Mean	.009***	.016***
Std	.021	.043
Min	-.065	-.126
Max	.113	.199
SR	1.459	1.272

*White (1980) Heteroskedastic consistent standard errors. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

The calculation of the *Difference* portfolio that is in Table 3.3 is displayed in equation 3.7:

$$\mathrm{R}_t = (4_t - 3_t) - (2_t - 1_t) \tag{3.7}$$

The first observation that is clear from Table 3.3 is that expectation 1, a positive relation between option returns and the mean reversion parameter, appears confirmed. One can anecdotally notice that for both the straddle and delta-hedged call returns, there is a direct, positive relation (for example, low HV-IV displays lower returns and a lower mean reversion parameter than high HV-IV). More importantly, a monthly regression is applied with the full range of double-sorted portfolios as the dependent variable (either straddle or delta-hedged call returns) and the mean reversion parameter as the independent variable:

$$\textit{Double-Sorted Returns}_t = \alpha + \beta_1 \textit{Mean Reversion}_t + \epsilon_t \tag{3.8}$$

In regard to the straddle (delta-hedged call) returns, β_1, the mean reversion parameter, is positive and equal to .095 (.008) and is significant at 5 percent in both instances, indicating that the mean reversion parameter has a significant, positive relation with double-sorted option returns, confirming expectation 1. This strong evidence gives good consideration to analysis expectation 3: combining the informational power of the difference between HV and IV and ISV in a trading strategy increases the option returns over solely using the difference between HV and IV. Therefore, one has to compare a long-short portfolio solely invested in high ISV stocks and a long-short portfolio solely invested in low ISV stocks. This difference is shown in the last column of Table 3.3 and is named the *Difference* portfolio.

Observing Table 3.4, the most important observation is that the mean difference between a long-short portfolio solely invested in high ISV stocks and a long-short portfolio solely invested in low ISV stocks is positive and significant at 1 percent, indicating that investing in high ISV stocks generates a larger return than investing in low ISV stocks in a long-short context. This might seem contradictory with the hypothesized positive relationship between option returns and ISV (which will be proven in the subsection *Stock Risk-Factors*). In actuality, the relation is not disconfirmed by Table 3.4: each low ISV portfolio, 1 and 2, displays larger returns than the comparative high ISV portfolio, respectively 3 and 4. The relation would only be contradictory with a portfolio that is solely long into low ISV stocks. With a long-short portfolio, the interaction with HV-IV creates an asymmetric effect that has caused it to be more profitable to invest in high ISV stocks, regardless of the higher return of low ISV stocks. The high ISV long-short portfolio produces larger returns because the short portfolio displays extremely negative returns, which is also implied by the very low mean reversion parameter.

In Table 3.4, the return of the long-short, double-sorted portfolio exclusively invested in high ISV stocks is compared to the return of the single-sorted portfolio on HV-IV. One can observe a significant at 1 percent increase in the mean return in the comparison between the single-sorted and double-sorted portfolios, for both the straddle (5.6 percent) and delta-hedged call returns (0.7 percent), with a similar increase in the standard deviation. The Sharpe Ratio therefore remains consistent or decreases slightly with the delta-hedged call returns, implying that the addition of ISV indeed does increase returns, but also the associated risk. Nevertheless, one can conclude that the returns of a trading strategy consisting of a double sort of stocks on the difference between HV and IV and ISV of the underlying stock significantly and positively increases the portfolio return over a single sort on the difference between HV and IV.

4 Control Factors

The results have now been established and are very promising. The research design of this papers revolves around three vital steps. The Section *Control Factors* will cover step 3: control the results for known risk-factor models, stock risk-factors, model specifications and transaction costs. This essentially constitutes asking whether those large returns, provided by the addition of ISV, are actually abnormal, are merely compensation for some form of (unknown) risk taken or simply disappear altogether after factoring in transaction cost. If the returns are systematic compensation for a taken risk or disappear after factoring in transaction costs, there is very good reason to believe that these results will hold, but if they simply constitute a *free lunch*, one would expect these results to disappear shortly as a result of arbitrageurs.

In the endeavour to investigate the returns, it is important to consider that there is no general formal theoretical model that can be applied to the cross-section of option returns, necessarily requiring flexibility. One such path is the assumption that option returns, to some extent, depend on similar risk factors and characteristics that are relevant in interpreting stock returns.

A total of four perspectives are applied to analyse the large returns provided by the addition of ISV, starting with running factor-model regressions with the Q5-factor model on the Difference and Optimized portfolio. The decision to use the Q5-factor model and not the more common Fama French 5-factor model will be explained further. Then it is explored to what extent stock risk-factors relate to variation in the option returns via cross-sectional regressions relative to the full sample of indidividual option data. Thirdly, the results are exposed to both varying effective spreads to quoted spreads and stock trading costs, to determine the extent to which transaction costs reduce the option returns. Lastly, the robustness of the option returns are checked against three important assumptions underlying the paper, the weighting method, moneyness range and time period chosen.

4.1 Risk Factors

Various specifications of a linear pricing model are employed as the independent variables, regressed on both the Difference and the Optimized portfolio of both the straddle and delta-hedged call portfolio returns. The goal of this exercise is to display that the option returns are not related to aggregate sources of risk. The two specifications of the linear pricing model consists either of solely the market return and the Q5-factor model by Hou, Mo, Xue and Zhang (2020). The reason to choose this factor model over the more commonly used Fama French 5-factor model or 6-factor model, is the finding by Hou, Mo, Xue and Zhang (2020) that the Q5-factor model not only substantially outperforms and subsumes the Fama French 6-factor model in a large set of testing deciles based on 150 anomalies, but also a very large set of other, important factor models. The Q5-factor model consists of five factors: the market return, size, investment, return on equity and expected growth.

The regression specification of the linear pricing model on the long-short portfolio of both the straddle and delta-hedged call portfolio returns has the form of equation 4.1:

$$\mathrm{R}_{pt} = \alpha_p + \beta_p' \mathrm{F}_t + \epsilon_{pt} \tag{4.1}$$

In this regression, Rp is the return spread on the straddle and delta-hedged call portfolios. The constant, α_p, is the most important variable to interpret in the context of risk-adjusted returns, as a statistically and economically significant alpha might lead to the conclusion that, after correcting for known, relevant risk factors, there is still abnormal return left. The size of the constant should therefore be interpreted as the magnitude of the abnormal return relative to the specified factor model. Ft are the factors, which, depending on the specification, will either be the market return or the Q5-factor model. If any of the independent variables is significant, this will indicate that the option return is captured by some form of known, aggregate risk.

Table 4.1: Option returns of both the Difference (D) and the Optimized (O) long-short portfolio relative to the Q5-factor model.

The goal of this exercise is to display that the option returns are not related to aggregate sources of risk. The two specifications of the linear pricing model consists either of solely the market return and the Q5-factor model by Hou, Mo, Xue and Zhang (2020) as independent variables and the straddle and delta-hedged call returns as dependent variables. The Q5-factor model consists of five factors: the market return, size, investment, return on equity and expected growth. The regression specification of the linear pricing model has the form:

$$R_{pt} = \alpha_p + \beta_p' F_t + \epsilon_{pt}$$

The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from the 4th of January 1996 until the 31st of December 2020.

	Straddles				**Delta-Hedged Calls**			
	D		**O**		**D**		**O**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	.088**	.074*	.158***	.147***	.014***	.012**	.016***	.015***
	(.038)	(.040)	(.005)	(.021)	(.005)	(.005)	(.003)	(.003)
Mkt-RF	.011	.017**	-.011**	-.004	-.000	.001	-.000	.000
	(.008)	(.009)	(.022)	(.006)	(.001)	(.001)	(.001)	(.001)
ME		-.002		-.004		-.001		-.000
		(.012)		(.006)		(.001)		(.001)
IA		.019		-.000		.001		-.000
		(.016)		(.011)		(.002)		(.001)
ROE		-.001		.012		.001		.000
		(.014)		(.007)		(.002)		(.001)
EG		.014		.007		.002		.001
		(.017)		(.013)		(.002)		(.002)

*White (1980) Heteroskedastic consistent standard errors in parentheses. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

The univariate and multivariate regression results are in Table 4.1. One can observe that the market factor is the only significant factor with respect to the straddle returns of the Optimized portfolio. In all other instances, the market factor has no explanatory power regarding the option returns, indicating that the portfolios are well diversified in relation to market risk. This was very similarly concluded by Goyal and Saretto (2009) and does not change with the addition of ISV. The sign of the market factor is ambiguous, changing between positive and negative, which is also similar to Goyal and Saretto. More important than this observation, is the clear statistical and economical significance over the full range of the univariate regressions of the alphas, which indicates that after adjusting for inherent market risk, there is still statistically and economically significant return that is not just a form of known aggregate risk. This is true for both types of strategies and both the Difference and Optimized portfolio.

Regarding the multivariate setting that includes the Q5-factor model as independent variables, this observation does not change. The only significant factor is the market factor with respect to the straddle returns and the Difference portfolio. Each alpha is slightly reduced in magnitude in comparison to the univariate setting, but each is still economically and statistically significant, leaving ample abnormal return that is not captured by aggregate risk. To conclude, the magnitude of the abnormal returns regarding each strategy is very close to the raw returns, with thus almost no part of the returns relating to aggregate risk.

4.2 Stock Risk-Factors

It will now be investigated to what extent the individual option returns are related to stock risk-factors, including the difference between HV and IV and ISV and the extent to which either the sorting factors or known stock risk-factors can explain those returns. The relevant regressions are applied to the full sample of 762,820 individual option returns.

The implementation is ensued with a two-step procedure, starting with a first-pass time-series regression of the individual option returns on the Q5-factor model to generate risk-adjusted beta's, which are used to calculate risk-adjusted option returns for each individual option. The second step is to apply monthly, cross-sectional regressions of the lagged stock risk-factors on the risk-adjusted, individual option returns. The regression procedure and specification is similar to that in Brennan, Chordia, and Subrahmanyam (1998):

$$\mathrm{R}_{it} - \hat{\beta}_i'\mathrm{F}_t = \gamma_{0t} + \gamma_t'\mathrm{Z}_{it-1} + \epsilon_{it} \tag{4.2}$$

Rit in equation 4.2 is the excess return of individual options, with *Ft* the Q5-factors and *Zit* the stock risk-factors. The beta's on the left-hand-side of the equation are estimated with the earlier described procedure, the first-pass time-series regression. In total there are seven stock risk-factors that are employed in the second stage of the regression procedure: the HV-IV variable, ISV, size, book-to-market (BM), momentum of the past six months, kurtosis and skewness. The log value of size and kurtosis is taken to correct for the possible effect of outliers (both have very large values and are strictly positive). The specified regression is applied on a monthly basis, with the stock risk-factors lagged one fiscal period to avoid a forward-looking bias. A t-test under null hypothesis equal to zero is applied, using Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors and a correction for twelve lags. The time-series average of the independent variables and the alpha is reported with their t-statistics.

Table 4.2: Option returns adjusted for stock risk-factors.

Rit in equation 4.2 is the excess return of individual options, with *Ft* the Q5-factors and *Zit* the stock risk-factors. The beta's on the left-hand-side of the equation are estimated with a first-pass time-series regression of the individual option returns on the Q5-factor model. In total there are seven stock risk-factors that are employed in the second stage of the regression procedure: the HV-IV variable, ISV, size, book-to-market (BM), momentum of the past six months, kurtosis and skewness. The specified regression is applied on a monthly basis, with the stock risk-factors lagged one fiscal period to avoid a forward-looking bias.

$$\mathrm{R}_{it} - \hat{\beta}_i'\mathrm{F}_t = \gamma_{0t} + \gamma_t'\mathrm{Z}_{it-1} + \epsilon_{it}$$

The sample consists of 762,280 individual options, over in total 8641 stocks from January 1996 until December 2020.

	Straddles			**Delta-Hedged Calls**		
	(1)	(2)	(3)	(1)	(2)	(3)
Alpha	.061**	-.018	.030	.002	.001	.007
	(.027)	(.057)	(.056)	(.002)	(.004)	(.004)
HV-IV	.123***	.121***	.144***	.015***	.016***	.018***
	(.021)	(.023)	(.022)	(.002)	(.002)	(.002)
ISV	-.088***	-.104***	-.070*	-.008***	-.010***	-.007**
	(.034)	(.037)	(.037)	(.002)	(.003)	(.003)
Size		.005	.004		.000	.000
		(.003)	(.003)		(.000)	(.000)
Mom		.007	.009		-.001	-.001
		(.025)	(.024)		(.002)	(.002)
BM		-.293	-.450		-.033	-.048
		(.563)	(.570)		(.037)	(.037)
Skew			-.004*			-.000***
			(.002)			(.000)
Kurt			-.025***			-.003***
			(.005)			(.000)

*White (1980) Heteroskedastic consistent standard errors in parentheses. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

The results are in Table 4.3. The first clear observation is that the alphas are relatively consistently not significant, implying that the return variation in at least the delta-hedged call returns is solely captured by the combination of HV-IV and ISV and with straddle returns by the combination of HV-IV, ISV and size, momentum and BM. One can also observe that HV-IV and ISV are both significant in all regressions, to varying degrees, indicating that ISV is a relevant addition to HV-IV in explaining the cross-section of option returns. More importantly, ISV consistently has a significant, negative relation with both type of option returns, confirming expectation 2, that there is a negative relation between option returns and ISV. Lastly, one can observe that the significance of ISV as an explanatory variable does decrease, for both type of returns, with the introduction of skewness and kurtosis, indicating that some part of the information in ISV is also captured by skewness and kurtosis. Nevertheless, regardless of that the option returns covary with those two factors, this covariance is not substantial enough to subsume the explanatory power of ISV in explaining the straddle and delta-hedged call returns.

4.3 Transaction Costs

There is a wealth of academic literature reporting that transaction costs in the options market can be very substantial and might be the explanation for the existence of abnormal returns. Abnormal returns relative to a risk-factor model that disappear after transaction costs have no practical relevance. Therefore, it is crucial to determine the magnitude of the effect of transaction costs under the specific context that the abnormal returns resulting from the addition of ISV have been established. The effect of transaction costs on the economical significance of the long-short straddle and delta-hedged call returns will be reviewed from a common angle, using two elements: option costs from the perspective of the effective spread relative to the quoted spread and stock trading costs.

First, the option costs from the perspective of the effective bid-ask spread relative to the quoted spread will be discussed. The analysis presented in this paper has made one important assumption: a call or put option was bought at the mid-point price. This might not be feasible in all circumstances. De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) conclude that effective spreads, most specifically for equity options, are large in absolute terms, but usually the ratio of effective to quoted spread is less than 0.5. Unfortunately, the author is in no position to access transactions data on option pricing (because of the OTC character of option trading), therefore, multiple effective spread magnitudes are assumed and tested, equal to 25%, 50% and 100% of the quoted spread.

What does this imply? Assuming the bid price is $5 and the ask price is $10, this subsumes several scenarios: for example, buy at $8.75 and sell at $6.25 (50 percent effective spread relative to quoted spread); buy at $10 and sell at 5$ (100 percent effective spread relative to quoted spread). For both type of option returns, this adjustment process is only applied at the start of the strategy, as the portfolio is eliminated with the expiration of the options in the money.

The second part revolves around the transaction costs resulting from stock trading, having to buy the underlying stock as part of both the straddle and delta-hedged call strategy. Under a long-short, straddle strategy the cost of buying the underlying stock is only incurred at expiration of the option. The magnitude of the cost is dependent on whether the stock is bought or sold, depending on the profitability of either the call or put option and therefore which is most attractive to exercise. With a delta-hedged call strategy, this is more complicated. The process with a delta-hedged call option strategy is more complicated. Shares have to be sold at initiation of the strategy and bought at the settlement of the call option. The amount of shares sold and bought is equal to the option delta at initiation.

Table 4.3: Impact of transaction costs on option returns.
The impact of transaction costs, consisting of option costs and stock trading costs, on option returns are analysed. Multiple effective bid-ask spread magnitudes are assumed and tested, equal to 25%, 50% and 100% of the quoted spread with respect to the option costs. These are incurred only at the initiation of the portfolio. The stock trading costs are incurred only at expiration for the straddle strategy and with the delta-hedged call strategy, incurred at both the initiation and the expiration of the option. The scenario in row 1 and 3 only analyses the effect of option costs, whereas the scenario in row 2 and 4 analyses the effect of both types of transaction costs. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	D				**O**			
		ESPR/QSPR				**ESPR/QSPR**		
	MidP	25%	50%	100%	MidP	25%	50%	100%
				Panel A: Straddles				
Alpha	.095***	.102**	.108***	.149***	.150***	.085***	.018	-.165***
	(.040)	(.041)	(.042)	(.049)	(.023)	(.024)	(.027)	(.042)
				Including Stock Trading Costs				
Alpha	.090**	.095**	.100**	.140***	.090***	.026	-.041*	-.225***
	(.039)	(.039)	(.041)	(.049)	(.021)	(.022)	(.025)	(.040)
				Panel B: Delta-Hedged Calls				
Alpha	.014***	.009*	.004	-.007	.016***	.007**	-.002	-.020***
	(.005)	(.005)	(.005)	(.006)	(.003)	(.003)	(.004)	(.004)
				Including Stock Trading Costs				
Alpha	.005	.000	-.005	-.016***	-.001	-.010***	-.018***	-.037***
	(.005)	(.005)	(.005)	(.006)	(.003)	(.003)	(.003)	(.004)

*White (1980) Heteroskedastic consistent standard errors in parentheses. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

The effective spread, ergo, the stock trading cost, is calculated in accordance with equation 4.3. The trading, bid and ask price are taken from CRSP:

$$Effective\ Spread = (Price - ((Ask + Bid)/2) * 2 \quad (4.3)$$

The results are in Table 4.3. In line with Goyal and Saretto (2009), transaction costs substantially hit the return of the Optimized portfolio. Looking only at option costs, an effective spread to quoted spread of 50 percent is sufficient to reduce returns to zero for both types of returns. By including stock trading costs, one can observe that an effective spread of 25 percent is sufficient in regard to the straddle return and for delta-hedged calls trading at the midpoint is not even profitable any more.

This does show that transaction costs might evaporate any possible returns of a double-sorted portfolio strategy, especially if the effective spread is large (close to 50 percent). In the context of options, this is not an unsurprising result, and it gives a slight indication that the earlier abnormal returns exist because transaction costs prevent an arbitrageur to profit from them. Depending on the expected level of transaction costs, the strategy might or might not be statistically and economically significant.

Interestingly, in regard to straddle returns the difference in return between high and low ISV is maintained, even if the trading costs increase (with delta-hedged call returns this observation is less clear). Despite the significant, negative effect of transaction costs on the double-sorted portfolio returns, this does indicate that the relevance of ISV barely decreases with an increase in transaction costs.

4.4 Robustness

One inevitable consequence of doing research, is making assumptions. The results presented in this paper are linked to decisions made about key variable definitions and procedures. In this section, it will be shown that the results are independent of key assumptions made. Three topics will be discussed: the decision between value-weighting and equal-weighting long-short portfolios, the width of the moneyness range and the time period chosen.

Table 4.4: Optimized portfolio returns under equal-weighting and under value-weighting.

The *Optimized* portfolio is long in the portfolio with stocks with the largest, positive difference between HV and IV and the highest ISV and short the portfolio with the largest, negative difference and the highest ISV. The weight under value-weighting is determined by the log value of the market capitalization of a firm. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Equal-Weighted	**Value-Weighted**
Panel A: Straddle Returns		
Mean	.150***	.085***
Std	.348	.492
Min	-.863	-2.302
Max	2.657	2.613
SR	1.497	.595
Panel B: Delta-Hedged Call Returns		
Mean	.016***	.009**
Std	.043	.073
Min	-.126	-.366
Max	.199	.373
SR	1.272	.405

*White (1980) Heteroskedastic consistent standard errors. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

4.4.1 Value-Weighting

Traditionally, there has always been a rift between value weighting and equal-weighting. Equal-weighting is usually applied as the first method in academic research, because commonly it will provide larger returns and a larger t-statistic than value-weighting, establishing a first indicator of truth relative to an hypothesis. On the other hand, actually implementing an equal-weighted strategy is much more costly: one constantly has to update the portfolio to maintain an equal weight for each share, whereas with value-weighting this is not the case. Therefore, it is also important that the option returns are researched under a value-weighted portfolio construction process, especially in the light of one of the goals of this paper: to provide practitioners with relevant information. The portfolio construction process is exactly applied as described before, except that the weight of each option is determined by the lagged market value of the underlying stock. The result is in Table 4.4

The decision to either use equal-weighting or value-weighting has a substantial impact on both type of option returns, in mean return, standard deviation and Sharpe Ratio. The mean return almost halves, while the standard deviation increases, which has a similar result on the standard deviation. One can also observe that the extreme values become more extreme. Nevertheless, the straddle returns are still significant at 1 percent and the delta-hedged call returns still significant at 5 percent. The chosen weighting method has its effect on the economical significance of the double-sorted portfolio returns, but it remains statistically significant. This is not only true for the double-sorted portfolio returns, but also for the single-sorted returns on HV-IV.

4.4.2 Moneyness

The reason to choose a very narrow range of moneyness has been discussed earlier in the data section. The initially chosen range of moneyness is from 0.95 to 1.05 and is now changed to 0.9 and 1.1. The result is an increase in the amount of monthly option pairs from 381,410 to 458,592 and from 8641 stocks to 8832 stocks. Nevertheless, the actual raw returns barely change at all (only a small increase), certainly not significantly.

4.4.3 Time Period

This paper concluded that the hypothesis of Goyal and Saretto (2009) can be extended to the range of years from 1996 until 2020 and that ISV is a relevant addition. One should still be cautious: it might very well be that this conclusion only applies to the time period studied by Goyal and Saretto (2009), 1996 until 2006 and that after that, the returns are not significant any more, despite the average over the time period 1996 until 2002 being significant. Therefore, it is relevant to split the total data into two subsamples: from 1996 until 2006 and from 2007 until 2020 and compare the double-sorted portfolio returns. The results are in Table 4.5 on the next page.

Table 4.5: Optimized portfolio returns prior to 2006 and after 2006.
The *Optimized* portfolio is long in the portfolio with stocks with the largest, positive difference between HV and IV and the highest ISV and short the portfolio with the largest, negative difference and the highest ISV. The sample consists of 381,410 monthly pairs of put and call contracts, over in total 8641 stocks from 1996 until 2020.

	Prior 2006	**After 2006**
	Panel A: Straddle Returns	
Mean	.193***	.116***
Std	.321	.368
Min	-.833	-.810
Max	1.518	2.657
SR	2.086	1.091
	Panel B: Delta-Hedged Call Returns	
Mean	.024***	.009***
Std	.049	.037
Min	-.121	.118
Max	.209	.120
SR	1.724	.820

*White (1980) Heteroskedastic consistent standard errors. ***, **, * show that a coefficient is significant respectively on a 1, 5 and 10 percent level.*

The clear observation is that after 2006, the double-sorted portfolio returns are substantially lower for both types of returns, with more extreme values and a lower Sharpe Ratio. Nevertheless, both types of returns remain significant at 1 percent. This pattern is not only observed for the double-sorted portfolio returns, but also for the single-sorted returns on HV-IV, indicating that it is not simply the result of ISV becoming less relevant. One important question is what this predicts about the future: can one expect these returns to disappear at some point altogether? And what has caused this decline so far? The former will need more years of data to develop a conclusion, the latter might be the subject for a new research paper. Could it be that practitioners have already implemented the Goyal and Saretto (2009) hypothesis in their trading model?

5 Conclusion

In this paper, the following hypothesis was tested: a double sort of stocks on the difference between HV and IV and ISV of the underlying stock significantly and positively increases the portfolio return over a single sort on the difference between HV and IV, robust to known risk-factor models, stock risk-factors, model specifications and transaction costs.

Using a dataset that extends from the 4th of January 1996 until the 31st of December 2020, it is concluded that the hypothesis of Goyal and Saretto (2009) extends to the present day (albeit with a smaller magnitude of 9.6 percent monthly straddle return) and more importantly, that it is outperformed by a zero-cost trading strategy involving a long position in the option portfolio with stocks with a high ISV and a large, positive difference between HV and IV and a short position in the option portfolio with stocks with a high ISV and a small, negative difference between HV and IV, displaying a monthly straddle return of 15 percent, thereby confirming expectation 3. At the basis of this observation is the finding that there is a significant difference in long-short option returns between high and low ISV stocks, which explains the decision to solely invest in high ISV stocks. In addition, expectation 1 is confirmed by directly regressing the mean reversion parameter on the double-sorted portfolio returns on a monthly basis and establishing a significant, positive relation between mean reversion and option returns.

The next step was to relate the option returns to aggregate risk factors (Q5-factor model) and stock risk-factors. Only the market factor under two specific circumstances displays significance in explaining the abnormal, double-sorted portfolio returns and all other factors relate in no way significantly to the abnormal returns. Even more so, the abnormal returns are very close to the raw returns, with thus almost no part of it relating to aggregate risk captured by the Q5-factor model. With respect to the stock risk-factors, a cross-sectional regression using the full sample is applied, with the straddle and delta-hedged call returns as the dependent variable and HV-IV, ISV and six other stock variables as the independent variables. All alpha's but one are insignificant, indicating that all variation in the option returns can be captured by the combination of HV-IV and ISV and certain stock variables, where HV-IV and ISV are significant in each regression with varying variables. This also indicates that ISV is a relevant addition to HV-IV in explaining option returns and more importantly, the significant, negative relation between the option returns and ISV confirms expectation 2.

Observing a significant, negative relation between the option returns and ISV, while only investing in high ISV stocks might seem contradictory, but this would only be true with a portfolio that is solely long into low ISV stocks. With a long-short portfolio, the interaction with HV-IV creates an asymmetric effect that has caused it to be more profitable to invest in high ISV stocks, regardless of the higher return of low ISV stocks, because with the long-short portfolio, one can profit from extreme underperformance of high ISV stocks.

In line with Goyal and Saretto (2009), transaction costs significantly reduce the profitability of the trading strategy. Assuming an effective spread to quoted spread of 50 percent is sufficient to reduce returns to zero for both types of returns. Including stock trading costs, 25 percent is sufficient in regard to the straddle return and with delta-hedged calls, trading at the midpoint ceases to be profitable. This shows that transaction costs might evaporate any possible returns of a double-sorted portfolio strategy, especially if the effective spread is large (close to 50 percent). Depending on the expected level of transaction costs, the strategy might or might not be statistically and economically significant. Interestingly, the difference in return between high and low ISV is maintained, even if the trading costs increase.

The double-sorted portfolio returns are robust to the weighting method, moneyness range and time period chosen. The decision to either use equal-weighting or value-weighting does have impact on both the straddle and delta-hedged call returns, reducing the monthly mean return from 15% and 1.6% respectively to 8.5% and 0.9%. Nevertheless, the straddle returns are still significant at 1% and the delta-hedged call returns still significant at 5%. Changing the moneyness range from being between 0.95 and 1.05 to 0.9 and 1.1 has barely effect on the actual raw returns, despite a minor increase, certainly not significantly. Lastly, the sample period is split into two subsamples, before and after 2006, therefore equal to the period studied by Goyal and Saretto (2009) and all years that they have not studied in their paper. The observation is that after 2006 the double-sorted portfolio returns are lower for both types of returns, with more extreme values and a lower Sharpe Ratio. Nevertheless, both types of returns remain significant at 1 percent. This pattern, a substantial decrease in return, is not only observed for the double-sorted portfolio returns, but also for the single-sorted returns on HV-IV. The author therefore concludes that the addition of ISV is promising and that the hypothesis is confirmed to a large extent, but is accompanied by a practical caveat in the transaction costs.

A critical note on the research design concerns the data on the stock trading costs. Goyal and Saretto (2009) used the inter-day transactions data from TAQ, whereas this paper used the closing ask and bid prices from CRSP. The reason for this deviation is that for the size and scope of the options dataset, garnering matching TAQ data proved to be too difficult because of the sheer size of the data required. The TAQ data would have been more exact, but it was practically not feasible.

One could still ask: to what extent does one expect that this strategy will still provide significantly positive risk-adjusted returns in the future? The answer to this question lies in what drives the abnormal return: is it an (unknown) aspect of risk, that is at least not captured by the Q5-factor model and stock risk-factors, or does it constitute a "free lunch", return without risk. If the former is true, there is very good reason to believe that these results will hold, but if the latter is true, one would expect these results to disappear shortly as a result of arbitrageurs. The reality is that the reason for the observed empirical regularity is unclear. Most of the variation in the return is not related to an obvious source of risk, either a risk factor or a stock risk-factor. The hypothesis and theoretical background of this paper pointed, as did Goyal and Saretto (2009), to a behavioural explanation, which would deem it a "free lunch", because it is a result of irrational market behaviour. To a large extent this was confirmed, and it would also explain why the magnitude of the regularity has decrease in recent years: arbitrageurs are taking their "free lunch". Still, a critical note can be found in the presence of transaction costs, which were able to remove any possible returns at reasonably high levels. Therefore, it might be practically impossible to profit from the abnormal returns for arbitrageurs. Both explanations, either the behavioural perspective or transaction costs, are plausible.

With this in mind, two things would be very interesting concerning future research: Delve deeper into the behavioural explanation, using the behavioural framework set up by this paper, to either confirm or disconfirm the behavioural explanation of the abnormal, option returns. Closely related to this, one can also focus on the significant difference in double-sorted option returns before and after 2006. What may have caused this change, does it give any predictions about the future of this regularity, and does it provide an explanation on the cause of the abnormal returns?

References

Poteshman, A. M., & Serbin, V. (2003). Clearly Irrational Financial Market Behavior: Evidence from the Early Exercise of Exchange Traded Stock Options. *The Journal of Finance, 58*(1), 37-70.

Andersen, T., Bollerslev, T., Christoffersen, P. & Diebold, F. (2006). Volatility and Correlation Forecasting. In G. Elliott (Ed.), *Handbook of Economic Forecasting* (pp. 777-878). Amsterdam, The Netherlands: Elsevier.

Barberis, N., & Huang, M. (2002). Mental Accounting, Loss Aversion, and Individual Stock Returns. *The Journal of Finance, 56*(4), 1247-1292.

Brennan, M., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics, 49*(3), 345-373.

Cao, J. & Han, B. (2013). Cross-Section of Option Returns and Idiosyncratic Stock Volatility. *Journal of Financial Economics, 108*(1), 1-46.

Cao, J., Han, B., Tong, Q., & Zhan, X. (2021). Option Return Predictability. *The Review of Financial Studies, 34*(2), 569-1103.

De Font Nouvelle, P., Fishe, R. P. H., & Harris, J. H. (2003). The Behavior of Bid-Ask Spreads and Volume in Options Markets during the Competition for Listings in 1999. *The Journal of Finance, 58*(6), 2437-2464.

Driessen, J., Maenhout, P. J., & Vilkov, G. (2009). The Price of Correlation Risk: Evidence from Equity Options. *The Journal of Finance, 64*(3), 1377-1406.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*(1), 3-56.

Gao, C., Xing, Y., & Zhang, X. (2018). Anticipating Uncertainty: Straddles Around Earnings Announcements. *Journal of Financial and Quantitative Analysis, 53*(6), 2587-2617.

Goyal, A. & Saretto, A. (2009). Cross-section of option returns and volatility. *Journal of Financial Economics, 94*(2), 310-326.

Hou, K., Mo, H., Xue, C., & Zhang, L. (2020). *An Augmented q-Factor Model with Expected Growth*. Review of Finance. Available at: https://papers-ssrn-com.eur.idm.oclc.org/sol3/papers.cfm?abstract$_id = 3525435$.

Hwang, S. & Rubesam, A. (2013). A behavioral explanation of the value anomaly based on time-varying return reversals. *Journal of Banking Finance, 37*(7), 2367-2377.

Loughran, T., & Wellman, J. W. (2011). New evidence on the relation between the enterprise multiple and average stock returns. *Journal of Financial and Quantitative Analysis, 46*(6), 1629-1650.

Newey, W. K. & West, K. D. (1987). A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica, 55*, 703-708.

Stein, J. (1989). Overreactions in the Options Market. *The Journal of Finance, 44*(4), 1011-1023.