A New Look at the Low-Volatility Effect in Stock Options [¶]

Olaf Korn,[*] Niklas Trappe,[‡] and David Volkmann[§]

August 2019

[¶]We would like to thank Jelena Eberbach, Michael Hofmann, Philipp Schuster, and Marliese Uhrig-Homburg for their helpful comments and suggestions. Special thanks go to Bing Han for providing detailed information on data filters employed in Cao and Han (2013). This work was supported by the Deutsche Forschungsgemeinschaft [UH 107/4-1, KO 2285/3-1].

[*]Olaf Korn (corresponding author), University of Goettingen and Centre for Financial Research Cologne (CFR), Platz der Göttinger Sieben 3, D-37073 Göttingen, Germany; tel. +49 551 39 7265, fax +49 551 39 7665; email okorn@uni-goettingen.de. Olaf Korn is a professor of finance at the University of Goettingen and a research fellow at the Centre for Financial Research Cologne (CFR).

[‡]Niklas Trappe, University of Goettingen, Macquarie University and RoZetta Institute, Platz der Göttinger Sieben 3, D-37073 Göttingen; email niklas.trappe@uni-goettingen.de. Niklas Trappe is a researcher at RoZetta Institute and a PhD candidate at the University of Goettingen and Macquarie University.

[§]David Volkmann, University of Goettingen, Platz der Göttinger Sieben 3, D-37073 Göttingen, Germany; tel. +49 551 39 7877, fax +49 551 39 7665; email dvolkma@uni-goettingen.de. David Volkmann is an associate quantitative analyst at FinCAD and a PhD candidate at the University of Goettingen.

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Abstract

A widespread anomaly in financial markets is the inverse relation between volatility and future returns: the low-volatility effect. We take a new look at this phenomenon in the market for equity options. Our empirical results show that the negative association between stock return volatilities and option returns is not a general pattern, but is conditional on market makers being net short in options. If they are net long, the effect can even be reversed. The conditional nature of the low-volatility effect in option markets stresses the importance of market imperfections and the reaction of market makers in explaining the anomaly. Moreover, the conditional low-volatility effect contains important information for option market investors because it is three to four times stronger than the unconditional effect.

Key Takeaways:

- The low-volatility effect in stock options is a conditional effect that appears when market makers are net short in options.
- The conditional low-volatility effect is three to four times stronger than the unconditional low-volatility effect.
- The conditional low-volatility effect cannot be explained by common factor risks or market inefficiencies but stresses the importance of market makers and market imperfections for the low-volatility anomaly.

JEL Classification: G12; G13

Keywords: low-volatility effect, option returns, market imperfections

I Introduction

Volatility is negatively related to future returns. This empirical regularity, often called the low-volatility anomaly or the low-volatility effect, is one of the most interesting puzzles in financial economics and has been observed in many markets (Ang, Hodrick, Xing, and Zhang, 2006, 2009). Cao and Han (2013) have documented a specific variant of this anomaly: delta-hedged option returns decrease with an increasing idiosyncratic volatility (IVOL) of the underlying stock. In this paper, we provide new empirical evidence on the low-volatility effect in stock options that sheds new light on the economic forces behind the anomaly. By doing so, we contribute to a better understanding of the anomaly generally.

We propose and investigate the conditional low-volatility effect, arguing that a negative relation between stock volatility and future option returns is conditional on market makers being net short in options. If market makers are net long in options, there can be a converse relation, leading to a high-volatility effect. A reason for this conditional low-volatility effect is based on the idea that high IVOLs cause problems for market makers in option markets because they are accompanied by high volatility risk that cannot be hedged easily due to a lack of volatility derivatives for individual stocks. If there is end-user buying pressure, market makers need extra compensation in the form of higher prices for writing options on high-volatility stocks, driving option returns down. If there is selling pressure by end users and market makers need to buy options, then option prices need to be lower, leading to higher returns for options on high-volatility stocks. The effect may not be symmetric, however. As short positions in options impose a higher risk on market makers than long positions in terms of maximum losses, the low-volatility effect could be stronger than the high-volatility effect, causing an inverse relation between volatility and option returns on average—that is, an unconditional low-volatility effect.

Our empirical results provide clear evidence for a conditional low-volatility effect.

An inverse relation between stock volatility and future option returns holds for a fraction of options only. Using double-sorts based on stock volatility and a proxy for market-maker positions, only those quintiles where market makers are most likely to hold short positions show a low-volatility effect. For the quintiles where market makers are most likely net long in options, the effect can be reversed. This conditional high-volatility effect, however, is much weaker than the conditional low-volatility effect and not statistically significant. Due to this asymmetry, the average (unconditional) relation shows increasing mean option returns with decreasing stock volatility, confirming the results by Cao and Han (2013). Separation between systematic volatility (SVOL) and idiosyncratic volatility (IVOL) via a one-factor market model reveals that IVOL is the crucial component. When separation is instead based on the three-factor model by Fama and French (1993), SVOL also leads to significant effects. We interpret these findings as evidence for unhedgeable volatility risk—that is, non-market volatility risk, being an important economic driver of the low-volatility effect.

The results of our paper contribute to a better economic understanding of the low-volatility effect by providing new evidence on the importance of market makers—facing market frictions and market incompleteness—in the relation between stock volatility and option returns. Our analysis also offers new insights for investors. If investors want to integrate the low-volatility effect in stock options into their trading strategy, they could just concentrate on a fraction of options: those that actually show this pattern. Moreover, the conditional effect is about three to four times stronger than the unconditional one. Because the conditioning variable that we use in our empirical study requires knowledge of historical stock and option prices only, the necessary information is relatively easy to obtain. To investigate the potential benefits for investors in more detail, we check whether the conditional low-volatility effect is related to common factor risks in stock and options markets and whether it remains stable over time. Finally, we explore if it is strong enough to be exploited via a simple long–short trading strategy under transaction costs.

Our paper contributes to two strands of literature. First, it belongs to the group of studies that investigate the low-volatility effect. Different explanations for this effect have been put forward in the literature. One line of argument points to the extra demand for high-volatility assets, caused either by leverage constraints that investors have to meet (Frazzini and Pedersen, 2014), the irrational behavior of private investors (Mohrschladt and Schneider, 2018), or speculative demand due to investor preferences for lottery-like payoffs (Bali, Cakici, and Whitelaw, 2011; Bali, Brown, Murray, and Tang, 2017). Such speculative demand is also what Cao and Han (2013) have in mind as a reason for the low-volatility effect in option markets.[1] Our suggestion of a conditional low-volatility effect is fully consistent with these demand-based explanations. However, we broaden the picture by looking at the supply side and ask how costly it is to meet a specific demand. Even if end-user demand for high-volatility stocks and low-volatility stocks were equal, if market makers have to bear higher costs to meet the demand for high-volatility stocks, then there is still a low-volatility effect. This change of perspective from demand towards the balancing of supply and demand may also be fruitful for analyses of the low-volatility effect in other markets.

Second, our paper contributes to the literature on the cross section of expected option returns. Most importantly, it shows that two well-known return patterns—the low-volatility effect, as discovered by Cao and Han (2013), and the "expensiveness effect" by Goyal and Saretto (2009)—are closely related, because expensiveness serves as a conditioning variable to proxy market-maker positions in our study. Our paper also complements other results on specific regularities in option returns by stressing the importance of conditioning on market-maker positions (Kanne, Korn, and Uhrig-Homburg, 2018), the importance of the different risk profiles of long versus

[1] Further evidence on the relation between lottery-like preferences and option returns is provided by Byun and Kim (2016).

short positions in options that are reflected in margin requirements (Hitzemann, Hofmann, Uhrig-Homburg, and Wagner, 2018), and the general importance of market imperfections for the understanding of the cross section of expected option returns (Christoffersen, Goyenko, Jacobs, and Karoui, 2018).

Our paper is structured as follows: In Section II, we introduce the conditional low-volatility effect and develop hypotheses for our empirical investigation. Section III describes our data set and the data processing. Next, we present our main results on the conditional low-volatility effect in Section IV. In Section V, we provide additional results, centering on the extent to which the effect is beneficial for investors. Section VI concludes.

II Volatility and Imperfect Markets: The Conditional Low-Volatility Effect

This paper takes a new look at the economic forces behind the low-volatility effect in options markets. In particular, it investigates a potential link between the low-volatility effect and market imperfections. Market imperfections and volatility are related because stochastic IVOL is an important non-hedgeable risk for market makers, and the magnitude of volatility risk is likely to grow with the volatility level.[2] Non-hedgeable risks lead to inventory risk, and inventory risk can have significant effects on option prices and returns (Gârleanu, Pedersen, and Poteshman, 2009). Does such a link, however, suffice to constitute a low-volatility effect? Should delta-hedged option returns be lower or higher when market imperfections are more severe? That is, should option returns decrease or increase with growing stock

[2]This latter point is in line with standard option pricing models. In the model by Heston (1993), variance risk is proportional to volatility. In the model by Christoffersen, Fournier, and Jacobs (2018), both market variance risk and idiosyncratic variance risk are proportional to market volatility and IVOL, respectively.

volatility? In our view, the answer depends on whether market makers are net long or net short in options. If there is end-user buying pressure and market makers end up with net short positions in options, market imperfections should lead to higher option prices and lower returns. Therefore, option returns should decrease with stock volatility and there is a low-volatility effect. If market makers are net long, however, higher stock volatilities should be associated with higher option returns and there is a high-volatility effect. This argument leads to our first hypothesis.

Hypothesis 1: *Delta-hedged option returns decrease with stock volatility in the cross section for options with net short positions of market makers, leading to a low-volatility effect. For options with net long positions of market makers, option returns increase with stock volatility, leading to a high-volatility effect.*

Hypothesis 1 conjectures a low-volatility effect that is conditional on the net position of market makers being negative. Conversely, if market makers are net long, a positive relation between volatility and option return should appear: that is, stocks with higher volatility will have options with higher expected returns. However, the two settings of negative versus positive net positions of market makers may not be symmetric. Consider a market maker who has bought a call option. The downside risk of this position is capped at the option premium. In contrast, if the market maker had written the call, the downside risk of the position is unlimited. Such differences between long and short positions in terms of risk are also reflected in margin requirements, leading to different margin costs. It is therefore reasonable to conjecture that stock volatility affects option returns more severely if market makers have to deal with short positions, as stated in our second hypothesis.

Hypothesis 2: *The relation between stock volatility and option returns is not symmetric with respect to a net short or net long position of market makers: the* *conditional low-volatility effect is stronger than the conditional high-volatility effect.*

If Hypothesis 2 were true, it could resolve the empirical puzzle of an unconditional low-volatility effect that is associated with market makers being net long on average (over all stocks) in stock options (Ni, Pan, and Poteshman, 2008; Muravyev, 2016; Christoffersen, Goyenko, Jacobs, and Karoui, 2018).[3] If more stocks show a high-volatility effect (market makers being net long in stock options) than low-volatility effect (market makers being net short in stock options), but the latter effect is much stronger, then the unconditional effect could well be a negative relation between stock volatility and delta-hedged options returns.

When investigating the link between stock volatility and option returns, conditioning on the market-maker position is not the only issue to consider. It is also crucial to be precise about the relevant volatility concept. Because it is non-hedgeable risk that causes problems for market makers' inventories, the hedgeable and non-hedgeable parts of volatility should be distinguished. This distinction is not necessarily the same as that between SVOL and IVOL, however, because the latter depends on the specific factor model employed in an empirical study. If market imperfections are the root cause of the low-volatility effect, then what matters should be the availability of liquid hedging instruments for volatility risk, leading to our third hypothesis.

Hypothesis 3: *Only volatility risk that cannot be easily hedged via volatility derivatives is relevant for the low-volatility effect.*

Hypotheses 1 to 3 take the perspective that market imperfections are at the heart of the low-volatility effect. Even if these hypotheses are supported empirically, potential alternative explanations for the conditional low-volatility effect are still to

[3]However, these studies also show a very large variation in market-maker positions between option series. That is, although market makers are net long on average, there are many stocks where market makers are net short in the respective options.

be considered. The reason is that these alternative explanations may have important consequences for investors. First, there is the question of whether the observed empirical patterns are at least partly explained by risk premiums for common factor risks. If investors try to incorporate options into factor-investing strategies, this information is key to making judgments about the potential to generate alpha and achieve diversification benefits. Second, is the conditional low-volatility effect big enough to offer significant trading profits even after accounting for common risks and transaction costs? If the answer is yes, then at least part of the effect could be a result of market inefficiencies. The question of whether such market inefficiencies still exist or were reduced over time is another important piece of information for investors. We investigate these issues in the penultimate section of this paper.

III Data and Data Processing

Data Sources and Filters

Our first major data source is the OptionMetrics IvyDB database. This database contains information on all US exchange-listed individual equity and index options. For our analysis, we use the daily closing bid and ask quotes of options written on individual stocks, deltas, implied volatilities (IVs), and the matching stock prices. Deltas and IVs are calculated by OptionMetrics's proprietary algorithms, which account for discrete dividend payments and the early exercise of American options. OptionMetrics also provides 365-day historical return volatilities of the options' underlying stocks. The sample period for the options data is from January 1996 to August 2015.

We use similar data filters as in previous studies (e.g., Goyal and Saretto, 2009; Cao and Han, 2013; Kanne, Korn, and Uhrig-Homburg, 2018) to reduce the impact of recording errors. We drop all observations where the option bid price is zero, the bid price is higher than the ask price, the bid–ask spread is lower than the minimum tick size, and the mid price is smaller than \$1/8. Options written on stocks with an ex-dividend date during the option's remaining time-to-maturity as well as options that violate obvious no-arbitrage conditions are also excluded. Moreover, we require a non-missing delta, IV, and 365-day historical volatility (HV), to retain an observation in our sample.

Our second major data source is the Center for Research in Security Prices database. Daily stock returns from the database are matched with the options data to calculate historical 30-day stock volatilities. Finally, we use Kenneth French's database to obtain the returns of specific factor portfolios. These factor portfolios are required to distinguish SVOL from IVOL and to control for potential factor risk premiums. Risk-free interest rates are also taken from Kenneth French's database.

Delta-Hedged Option Returns

Following Cao and Han (2013), we take the end of each month and select for each underlying stock the put and call options that are closest to at-the-money and have the shortest remaining time-to-maturity of all options with a maturity of at least one month. We also require the actual moneyness to fall within the range $[0.8, 1.2]$, with moneyness measured as the ratio of spot price to strike. We then calculate delta-hedged option returns for calls and puts according to

$$R^C_{t,t+\tau} = \frac{\max\left(S_{t+\tau} - K^C,\, 0\right) - \Delta^C_t S_{t+\tau} - \left(C_t - \Delta^C_t S_t\right) e^{r\,\tau}}{Abs(C_t - \Delta^C_t S_t)}, \tag{1}$$

$$R^P_{t,t+\tau} = \frac{\max\left(K^P - S_{t+\tau},\, 0\right) - \Delta^P_t S_{t+\tau} - \left(P_t - \Delta^P_t S_t\right) e^{r\,\tau}}{Abs(P_t - \Delta^P_t S_t)}, \tag{2}$$

where t refers to the day when we set up the delta-hedged option position (end of month) and $t + \tau$ is the last trading day of the option. S_t and $S_{t+\tau}$ denote the matched prices of the underlying stock at times t and $t + \tau$, respectively, K^C and K^P are the options' strike prices, and Δ_t^C and Δ_t^P denote the deltas. The option prices C_t and P_t are the closing mid prices at date t. According to Equations (1) and (2), we use the returns of delta-hedged call and put options that buy one option contract and sell delta shares of the underlying stock. The above return definitions also consider that a positive initial value (at date t) of a delta-hedged option requires some capital which could alternatively be invested at the risk-free rate. If the initial value is negative, the delta-hedged option provides some capital that could alternatively be obtained via risk-free borrowing. Because our delta-hedged option returns take these opportunities for risk-free investing or borrowing into account, they are to be interpreted as excess returns.

[Insert Table 1 about here]

Given our data period and the data filters, we have 357,551 delta-hedged call returns and 359,136 delta-hedged put returns. As the data period covers 236 months, we have on average 1,515 calls and 1,522 puts in a cross section. However, the number of observations per cross section increases over time. Panels A and B of Table 1 provide some descriptive statistics of the delta-hedged call and put returns. Average delta-hedged returns are negative for both calls and puts and show a very large dispersion. The return period (time-to-maturity of options) is, on average, close to 50 days and the moneyness of the options is close to one.

Stock-Return Volatilities

To investigate the cross-sectional relation between option returns and stock volatilities, we need to calculate volatilities in a next step. Again, we closely follow Cao and Han (2013). For every stock and every date t, we calculate the standard deviation of daily stock returns over the previous 30-day period.[4] This is our measure of total volatility (VOL). To separate IVOL from SVOL, we use either the market factor or the three-factor model by Fama and French (1993).[5] Because liquid derivatives contracts are available to hedge changes in market volatility—for example, futures on the Chicago Board Options Exchange Volatility Index (VIX)[6]—the one-factor model should be more appropriate than the three-factor model in distinguishing between hedgeable and non-hedgeable[7] volatility risk. This is what we will exploit to test Hypothesis 3. Panel C of Table 1 shows some descriptive statistics of the (annualized) volatilities that we use in our study. On average, IVOL is greater than SVOL whether the one- or three-factor model is used. We also see the extent to which the three-factor model changes IVOL versus SVOL values compared to the one-factor model.

Conditioning Variables

The core idea of this paper is that the low-volatility effect should be investigated conditionally by considering whether market makers are net long or net short in specific options. To proxy market-maker positions, we take a pragmatic view and use a conditioning variable that is based on the market prices of stocks and options. Such a conditioning variable, based on public information only, has the advantage that a corresponding conditional low-volatility effect could be exploited more easily via trading strategies. No proprietary information on the actual holdings of market makers is required. The proxy that we use is option expensiveness, measured as the difference between the option's IV and a benchmark volatility estimate from

[4]To maintain a sufficient number of observations, we require to have at least 17 daily returns available over this period.

[5]We use the daily data from Kenneth French's database to obtain factor returns that exactly match the return periods of the options.

[6]More information on VIX futures is provided, for example, by Shu and Zhang (2012) and Simon and Campasano (2014).

[7]Volatility derivatives are not generally available for individual stocks and factor portfolios besides the market factor.

historical stock-return data (i.e., HV). As shown by Bollen and Whaley (2004) and Gârleanu, Pedersen, and Poteshman (2009), there is a strong relation between end-user demand pressure and expensiveness, which affects market-maker positions. The higher the expensiveness of an option, the more likely it is that market makers are net short in this option. The implementation of the expensiveness measure uses the date t IVs of the call and put options from OptionMetrics. For the HV benchmark, we use OptionMetrics's 365-day volatility for the period preceding date t, as in Goyal and Saretto (2009). Descriptive statistics for the expensiveness measure IV−HV are provided in Panel D of Table 1. In the latter part of our paper, we provide results that are conditional on different transaction cost scenarios. The core element of these scenarios is the option's quoted spread. Descriptive statistics for quoted spreads are also provided in Panel D of Table 1.

IV The Conditional Low-Volatility Effect: Empirical Evidence

For each month in our data period, we take all delta-hedged call (put) returns and sort them into quintiles according to the corresponding stock volatility. We use either VOL, IVOL, or SVOL in this sort. A single sort by volatility provides evidence on the unconditional low-volatility effect. Next, we sort the returns in each volatility quintile by IV−HV and again build quintiles. The purpose of this second sort is an (approximate) conditioning on net market-maker positions. With higher expensiveness, options in the respective quintiles should have a higher likelihood of market makers holding short positions. In contrast, if expensiveness is lower, market makers should more likely be net long in the corresponding options. For each of the 25 resulting groups, we calculate average returns. Finally, we obtain time-series averages of the average returns in each group.

Table 2 provides the results of these calculations, based on a one-factor market model to distinguish between IVOL and SVOL. Panel A presents the results for call options and Panel B the corresponding results for put options. The first five columns (1-low to 5-high) refer to the different expensiveness quintiles, and the last column (all) shows the average returns over all expensiveness categories; that is, it provides the results of the single sort by volatility. Therefore, the last column delivers information on the unconditional low-volatility effect. The first five rows (1-low to 5-high) refer to the respective volatility quintiles. The sixth row (5-1), contains the average returns of a long–short trading strategy that buys the high-volatility portfolio (5-high) and sells the low-volatility portfolio (1-low). If there is a low-volatility effect, the average return of this trading strategy should be negative. Positive returns of this trading strategy are indicative for a high-volatility effect. Finally, the seventh row shows the t-values for the average returns of the 5-1 portfolios.

[Insert Table 2 about here]

The results in Table 2 provide clear support for a conditional low-volatility effect, as stated in Hypothesis 1. Average delta-hedged option returns clearly decrease with total volatility for the two highest expensiveness quintiles. Moreover, the effect is much stronger for the highest expensiveness quintile. In terms of average 50-day returns of the 5-1 strategy, the effect is about three times bigger in the highest expensiveness quintile (–3.7%) than in the second highest expensiveness quintile (–1.2%) for call options. For put options, it is more than two times bigger (–2.4% versus –1.1%). However, no low-volatility effect can be found in the other three quintiles, meaning that the effect is only present in a fraction of the whole data set. Average returns of 5-1 strategies are even positive for the two lowest expensiveness quintiles, pointing towards a high-volatility effect. However, the effect is much smaller (in absolute terms) than the effect in the highest expensiveness quintiles and not statistically significant. This finding supports Hypothesis 2: a conditional high-volatility effect, if it exists at all, is much weaker than the corresponding conditional low-volatility effect. Consequently, the unconditional effect shows an inverse relation between stock volatility and future option returns, which was first discovered by Cao and Han (2013) and is confirmed by the results of the 5-1 strategy in the last column (all). It is also important to compare the magnitudes of the conditional and unconditional low-volatility effects. Examining the options with the highest expensiveness, returns of the 5-1 strategy are more than four times larger (in absolute terms) for calls (–3.7% versus –0.8%) and more than three times larger for puts (–2.4% versus –0.7%), as compared to a strategy based on all options.

In line with market imperfections being at the heart of the low-volatility effect in options markets, Hypothesis 3 states that only non-hedgeable volatility risk is relevant for the low-volatility effect. To provide evidence on this issue, we replace VOL with either SVOL or IVOL in our sorts. In particular, we use a one-factor market model to distinguish between the systematic and idiosyncratic parts of volatility. In such a setting, SVOL equals market volatility, and market volatility risk can be hedged via liquid volatility derivatives like VIX futures.

When using IVOL instead of VOL for sorting, the conditional volatility effect appears even stronger. If we condition on SVOL instead, there is no longer any significant low-volatility effect even in the highest expensiveness quintile. We interpret this finding as evidence for the dominant role of non-market volatility and non-hedgeable volatility risk, supporting Hypothesis 3. To further substantiate Hypothesis 3, we repeat our analysis of SVOL versus IVOL, this time using the three-factor model by Fama and French (1993) for separation. Table 3 provides our results. Given that the three-factor model differently defines IVOL and SVOL (compared to the one-factor model), the effects are slightly weaker for IVOL but stronger for SVOL. In the highest expensiveness quintile, we now find a significant low-SVOL effect for both calls and puts. By classifying volatility due to the two additional factors as systematic, SVOL becomes important for the low-volatility effect. This finding is consistent with the view that it is important whether market makers in options markets can easily hedge the corresponding volatility risk or not. Finally, it is worth noting that the effects of moving from a one- to a three-factor model cannot be observed by looking at the unconditional low-volatility effect alone. Therefore, our focus on the conditional low-volatility effect, which is much stronger in the highest expensiveness quintiles, helps us to study more subtle aspects of the whole phenomenon.

[Insert Table 3 about here]

V Benefits for Investors

In this section, we further explore the value of the conditional low-volatility effect for investors. Our first question is whether the returns of a conditional low-volatility trading strategy relate to some common factors that are priced either in stock or options markets. If the returns of such a strategy were merely compensation for common factor risks, then the value for investors is limited because more straightforward strategies exist to earn the respective risk premiums.

For our analysis of this question, we use a trading strategy that holds a long position in options on low-volatility stocks (1-low) and a short positions in options on high-volatility stocks (5-high), using the highest expensiveness quintile (5-high in Table 2) and IVOL according to the one-factor market model (IVOL-1F in Table 2). We consider both stock market factors and option market factors to explain the returns of this strategy. Although we try to avoid stock price exposure by using delta-hedged option returns, these hedges are unlikely to be perfect, and a remaining stock price exposure may be priced. To capture such effects, we use the three factors—market (MKT), size (SMB), and value (HML)—from the Fama and French (1993) model, the momentum factor (MOM) by Carhart (1997), and a low-volatility stock market factor (LowVol). The latter factor uses the returns of a long–short portfolio that buys low-volatility stocks and sells high-volatility stocks. The term "low-volatility stocks" refers to the 1-low quintile of all stocks according to IVOL (IVOL-1F in Table 2), and "high-volatility stocks" refers to the 5-high quintile of all stocks. Inclusion of the LowVol factor ensures that our results on delta-hedged option returns are not simply picking up the low-volatility effect in the stock market, due to our sorting by stock volatility. We also consider option market factors. The market volatility risk premium is approximated by the return of zero-beta straddles written on the Standard & Poors' (S&P) 500 Index (ZB-STR Index), as suggested by Coval and Shumway (2001). Changes in the VIX (dVIX) are used as an indicator for the magnitude of market volatility risk. In addition to market volatility risk, correlation risk may be priced in the low-volatility trading strategy. As shown by Driessen, Maenhout, and Vilkov (2009), correlation risk premiums can be captured via differences between the market variance risk premium and the average variance risk premium of the component stocks. Therefore, we add the average returns of zero-beta straddles written on all component stocks (ZB-STR Stocks) of the S&P 500 Index as an additional factor. All factor returns cover the same return periods as our delta-hedged option returns.

[Insert Table 4 about here]

Table 4 presents the results of time-series regressions that regress the delta-hedged option returns of the 1-5 strategy on different combinations of factors. Panel A gives the results for call options and Panel B for put options. Model 1 explores the impact of the stock market factors; Model 2, the importance of a market variance risk premium; Model 3, the impact of variance risk; and Model 4, the joint influence of variance and correlation risk premiums. Finally, Model 5 considers all factors simultaneously. The regression analysis shows some explanatory power for certain factors. Model 1 has significant coefficients for the MKT and HML factors, and Model 3 indicates some explanatory power of volatility risk. These results hold for both call and put options. For call options, there seems to be also an effect of the variance risk premium, according to Model 2. Most importantly, for all models in Table 4, alphas are highly significant and very close to the average return of a 1-5 strategy, which is 4.03% for calls and 2.67% for puts. Therefore, we can conclude that the cross-sectional phenomenon of a conditional low-volatility effect in option markets is not just a compensation for some common factor risks.

The second question that we ask in this section is whether the conditional low-volatility effect is only present in the early years of our data period and disappearing over time. If this were the case, the conditional low-volatility effect is likely to be a result of market inefficiencies that were reduced over time and should no longer be considered by investors. In particular, the Securities and Exchange Commission's (SEC's) market linkage plan, finally becoming effective in April 2003, may have contributed to the reduction of such inefficiencies. Moreover, we ask whether the positive average returns of our low-volatility trading strategy merely results from a few extreme observations during the financial crisis between June 2007 and December 2009, which would suggest that the conditional low-volatility effect would be irrelevant for investors in normal times.

[Insert Table 5 about here]

Table 5 provides the average returns and alphas (according to Model 5 in Table 4) for four different time periods. We consider the full period (January 1996 to August 2015), the full period excluding the time of the financial crisis from June 2007 to December 2009, the period until the SEC's market linkage plan became effective (January 1996 to April 2003), and the period thereafter (May 2003 to August 2015). There is no evidence that the conditional low-volatility effect is only driven by market inefficiencies during the early years of our data period. To the contrary, if we use the more recent data period from May 2003 onwards, both mean returns and alphas increase, as compared to the whole data period. This is true for both calls and puts.

If anything, the effect becomes stronger over time and there is no indication that it should be disregarded. There is also no indication that the effect is strongly driven by some extreme observations from the financial crisis. Excluding the crisis period, both average returns and alphas change very little.

The third question we deal with in this section is whether the conditional low-volatility effect can be exploited by investors via a simple trading strategy even in the presence of transaction costs. So far, our analysis of the low-volatility trading strategy was based on the assumption that trades can be executed at the mid quotes. Now we take option spreads into account and consider different transaction cost scenarios. We follow Cao and Han (2013) and assume that the effective spread (ESPR) of transactions equals a certain fraction of the quoted spread (QSPR).[8] Specifically, we assume ESPR/QSPR ratios of 10%, 25%, and 50%, respectively, following Cao and Han (2013). As a reference point, we also repeat results under the assumption of no transaction costs (i.e., mid price [MidP]).

[Insert Table 6 about here]

Table 6 reports the average delta-hedged option returns and alphas (according to Model 5 in Table 4) of the 1-5 portfolio in the highest expensiveness quintile under the different transaction cost scenarios. Panel A gives results for calls and Panel B gives results for puts. Average returns and alphas stay statistically and economically significant for an ESPR/QSPR ratio of 25%. If we move to 50%, however, we lose significance for both call and put options. In conclusion, only investors with low transactions costs can exploit the conditional low-volatility effect profitably, though the effect is three to four times stronger than that of unconditional low-volatility.

However, this finding does not mean that knowledge of the conditional low-volatility effect is useless for investors with higher transactions costs. To the contrary, our

[8]Compare Cao and Han (2013), page 246, Table 10, for analogous results with respect to the unconditional low-volatility effect.

findings show that the effect cannot be easily arbitraged away (due to the transactions costs) and does not tend to shrink over time, making it more likely that the effect will persist in the future and should be considered. For example, if investors with lottery-like preferences want to buy options on high-volatility stocks, they should think about selecting these options from the lowest IV−HV quintile (i.e., 1-low) instead of the highest one (i.e., 5-high). By doing so, they would avoid the strong low-volatility effect in the highest quintile and could even profit from the slight high-volatility effect in the lowest quintile. If we take the results from Table 2, the differences in average 50-day delta-hedged returns (using IVOL-1F) when selecting options on high-volatility stocks from the lowest IV−HV quintile instead of the highest quintile would be 6.5% for calls and 4.5% for puts.[9]

VI Conclusions

The low-volatility effect is a well-known phenomenon in many financial markets that challenges the intuitive idea of a risk–return trade-off. Our empirical investigation into the low-volatility effect in stock options contributes to a better understanding of this phenomenon. We show that the low-volatility effect is not a general pattern, but is conditional on option expensiveness being high. Where option expensiveness is low, the effect is even reversed, although the reverse effect is quantitatively much weaker.

Our empirical findings support the view that market imperfections and the reaction of market makers to these imperfections are at the heart of the effect. If high option expensiveness is a good proxy for market makers being net short in options and high IVOL is a good proxy for severe market imperfections, the observed pattern

[9]The calculations in Table 2 are based on mid quotes. If we take transaction costs into account and repeat the calculations based on ask prices, the differences in 50-day delta-hedged returns are 7% for calls and 4.9% for puts.

suggests that market makers receive a compensation because they sell at higher option prices if market imperfections become more severe. If market makers are net long, however, they receive a compensation because they buy at lower option prices. Because risk profiles of long and short positions in options are different, the former compensation should be greater, which is exactly what we observe. More generally, our analysis complements demand-based explanations of the low-volatility effect by drawing attention to the potential costs to meet a certain demand. This is an interesting avenue for further research in other markets as well.

The conditional low-volatility effect that we document in this paper also provides important information for investors in options markets. First, the conditional effect is three to four times stronger than the unconditional one. Second, it cannot be explained by common factor risks in stock and option markets and therefore offers some potential to create alpha. Finally, it is stable over time and cannot easily be arbitraged away in the presence of transaction costs. Therefore, the effect is likely to persist in the future and should be considered in the design of investment strategies in stock options.

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Table 1: Summary Statistics of Options and Stock Data

Panel A: Call Options (357,551 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.8%	14.9%	–14.4%	–8.1%	4.0%	14.2%
Days to Maturity	49.7	2.6	47.0	50.0	51.0	52.0
Moneyness (S/K)	1.00	0.06	0.94	0.97	1.03	1.06

Panel B: Put Options (359,136 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.4%	12.1%	–12.0%	–6.9%	3.8%	12.4%
Days to Maturity	49.7	2.6	47.0	50.0	51.0	52.0
Moneyness (S/K)	1.01	0.06	0.94	0.97	1.04	1.07

Panel C: Stock Return Volatilities

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
VOL	46.1%	30.5%	18.8%	26.2%	57.0%	81.9%
1-Factor Model (1F)						
IVOL-1F	39.1%	27.6%	14.8%	21.2%	49.0%	71.1%
SVOL-1F	20.7%	18.4%	4.3%	9.0%	26.3%	41.9%
3-Factor Model (3F)						
IVOL-3F	36.0%	25.7%	13.5%	19.4%	45.0%	65.7%
SVOL-3F	26.4%	20.1%	9.0%	13.6%	32.8%	49.8%

Panel D: Conditioning Variables

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Expensiveness: IV−HV	–0.8%	16.6%	–16.4%	–6.6%	5.6%	13.5%
Option Spread	27%	30%	6%	10%	31%	61%

Note: This table shows descriptive statistics of the options and stock data that we use in our empirical study. In particular, it presents the mean (μ), the standard deviation (σ), and different quantiles (10%-quantile ($q_{0.1}$), 25%-quantile ($q_{0.25}$), 75%-quantile ($q_{0.75}$), 90%-quantile ($q_{0.9}$)). Panel A shows the descriptive statistics for call options. Delta-hedged returns are calculated as given in Equation (1). Panel B shows the descriptive statistics for put options. The formula for these delta-hedged returns is given in Equation (2). Panel C provides descriptive statistics for historical stock return volatilities. These refer to annualized values from a historical 30-day data window, estimated from daily returns. We distinguish between total volatility (VOL), idiosyncratic volatility (IVOL), and systematic volatility (SVOL). The separation between SVOL and IVOL is either done via a one-factor market model (IVOL-1F, SVOL-1F) or via the three-factor model by Fama and French (1993) (IVOL-3F, SVOL-3F). Panel D presents descriptive statistics of the expensiveness measure, IV−HV, where IV denotes the implied volatility of the options, and HV is a historical 365-day benchmark volatility. Moreover, Panel D provides descriptive statistics of the quoted option spreads at the beginning of the return period, measured in percent of the mid price.

Table 2: Average Returns of Options Sorted by Stock Volatility and Expensiveness: One-factor Model

Panel A: Delta-hedged call returns

		Option Expensiveness (IV−HV)					
		1-low	2	3	4	5-high	all
VOL	1-low	0.3%	–0.3%	–0.4%	–0.7%	–1.8%	–0.6%
	2	0.6%	–0.2%	–0.6%	–0.8%	–2.5%	–0.7%
	3	1.1%	–0.1%	–0.5%	–1.0%	–2.7%	–0.7%
	4	1.0%	0.2%	–0.5%	–1.2%	–3.7%	–0.8%
	5-high	0.7%	0.1%	–0.5%	–1.9%	–5.5%	–1.4%
	5-1	0.5%	0.4%	–0.0%	–1.2%	–3.7%	–0.8%
	t-stat.	1.1	1.2	–0.1	–3.8	–10.0	–2.4
		1-low	2	3	4	5-high	all
IVOL-1F	1-low	0.4%	–0.4%	–0.4%	–0.6%	–1.7%	–0.6%
	2	0.6%	–0.1%	–0.5%	–0.8%	–2.4%	–0.6%
	3	0.9%	0.0%	–0.4%	–0.9%	–2.7%	–0.6%
	4	1.1%	0.2%	–0.4%	–1.2%	–3.8%	–0.8%
	5-high	0.7%	0.1%	–0.6%	–2.0%	–5.8%	–1.5%
	5-1	0.3%	0.5%	–0.1%	–1.3%	–4.0%	–0.9%
	t-stat.	0.8	1.5	–0.3	–4.5	–11.5	–3.0
		1-low	2	3	4	5-high	all
SVOL-1F	1-low	0.5%	–0.3%	–0.6%	–1.0%	–3.3%	–0.9%
	2	0.5%	–0.1%	–0.6%	–1.0%	–3.2%	–0.9%
	3	0.6%	–0.1%	–0.6%	–0.9%	–2.9%	–0.8%
	4	1.1%	–0.1%	–0.3%	–1.0%	–3.1%	–0.7%
	5-high	1.1%	0.0%	–0.3%	–1.2%	–3.8%	–0.9%
	5-1	0.5%	0.2%	0.3%	–0.2%	–0.5%	0.1%
	t-stat.	1.7	0.8	1.1	–0.9	–1.3	0.3

Panel B: Delta-hedged put returns

		Option Expensiveness (IV−HV)					
		1-low	2	3	4	5-high	all
VOL	1-low	0.4%	0.1%	0.0%	–0.3%	–1.4%	–0.2%
	2	0.7%	0.2%	–0.1%	–0.4%	–1.7%	–0.3%
	3	1.0%	0.3%	–0.1%	–0.5%	–1.8%	–0.2%
	4	1.0%	0.5%	0.1%	–0.7%	–2.6%	–0.4%
	5-high	0.6%	0.3%	–0.3%	–1.4%	–3.8%	–0.9%
	5-1	0.2%	0.1%	–0.3%	–1.1%	–2.4%	–0.7%
	t-stat.	0.5	0.4	–1.1	–4.0	–7.3	–2.7
		1-low	2	3	4	5-high	all
IVOL-1F	1-low	0.5%	0.1%	0.0%	–0.3%	–1.3%	–0.2%
	2	0.8%	0.3%	–0.1%	–0.4%	–1.6%	–0.2%
	3	1.0%	0.3%	–0.2%	–0.4%	–1.9%	–0.2%
	4	0.9%	0.4%	0.0%	–0.6%	–2.6%	–0.4%
	5-high	0.5%	0.3%	–0.4%	–1.4%	–4.0%	–1.0%
	5-1	0.0%	0.2%	–0.5%	–1.1%	–2.7%	–0.8%
	t-stat.	0.1	0.6	–1.9	–4.2	–8.9	–3.5
		1-low	2	3	4	5-high	all
SVOL-1F	1-low	0.6%	0.1%	–0.2%	–0.4%	–2.6%	–0.5%
	2	0.5%	0.2%	–0.1%	–0.7%	–2.2%	–0.5%
	3	0.7%	0.1%	–0.1%	–0.3%	–2.2%	–0.3%
	4	1.0%	0.3%	0.1%	–0.6%	–2.0%	–0.2%
	5-high	1.0%	0.3%	0.0%	–0.7%	–2.7%	–0.4%
	5-1	0.4%	0.2%	0.2%	–0.2%	–0.1%	0.1%
	t-stat.	1.6	0.9	0.9	–1.0	–0.3	0.5

Note: This table shows average delta-hedged options returns of portfolios sorted by stock volatility and expensiveness (IV−HV). Panel A shows the results for calls and Panel B the results for puts. For each month of the data period January 1996 to August 2015, delta-hedged option returns are sorted by volatility (either VOL, IVOL-1F or SVOL-1F). Within each volatility quintile, option returns are then sorted by expensiveness. The table reports the average delta-hedged returns for each volatility-expensiveness combination, averaged over time. The last column (all) provides averages over all expensiveness categories. The row denoted by 5-1 presents the results for a long–short trading strategy that buys the portfolios with the highest volatilities (5-high) and sells the portfolios with the lowest volatilities (1-low). The t-statistics for the average returns of these portfolios are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation of the portfolio returns.

Table 3: Average Returns of Options Sorted by Stock Volatility and Expensiveness: Three-factor Model

Panel A: Delta-hedged call returns

	Option Expensiveness (IV−HV)						
		1-low	2	3	4	5-high	all
VOL	1-low	0.3%	–0.3%	–0.4%	–0.7%	–1.8%	–0.6%
	2	0.6%	–0.2%	–0.6%	–0.8%	–2.5%	–0.7%
	3	1.1%	–0.1%	–0.5%	–1.0%	–2.7%	–0.7%
	4	1.0%	0.2%	–0.5%	–1.2%	–3.7%	–0.8%
	5-high	0.7%	0.1%	–0.5%	–1.9%	–5.5%	–1.4%
	5-1	0.5%	0.4%	0.0%	–1.2%	–3.7%	–0.8%
	t-stat.	1.1	1.2	–0.1	–3.8	–10.0	–2.4
		1-low	2	3	4	5-high	all
IVOL-3F	1-low	0.3%	–0.3%	–0.4%	–0.7%	–1.8%	–0.6%
	2	0.8%	–0.2%	–0.5%	–0.8%	–2.4%	–0.6%
	3	1.0%	0.1%	–0.4%	–0.9%	–2.7%	–0.6%
	4	1.1%	0.1%	–0.6%	–1.2%	–3.8%	–0.9%
	5-high	0.6%	0.2%	–0.7%	–1.9%	–5.7%	–1.5%
	5-1	0.3%	0.6%	–0.3%	–1.2%	–3.9%	–0.9%
	t-stat.	0.8	1.8	–0.7	–4.2	–11.2	–3.0
		1-low	2	3	4	5-high	all
SVOL-3F	1-low	0.5%	–0.3%	–0.5%	–0.8%	–2.7%	–0.8%
	2	0.4%	–0.2%	–0.7%	–0.9%	–2.9%	–0.9%
	3	0.7%	–0.1%	–0.6%	–0.9%	–3.1%	–0.8%
	4	1.1%	0.0%	–0.6%	–1.2%	–3.4%	–0.8%
	5-high	1.0%	0.2%	–0.2%	–1.2%	–4.5%	–1.0%
	5-1	0.4%	0.5%	0.2%	–0.4%	–1.8%	–0.2%
	t-stat.	1.2	1.4	0.6	–1.1	–5.2	–0.7

Panel B: Delta-hedged put returns

	Option Expensiveness (IV−HV)						
		1-low	2	3	4	5-high	all
VOL	1-low	0.4%	0.1%	0.0%	–0.3%	–1.4%	–0.2%
	2	0.7%	0.2%	–0.1%	–0.4%	–1.7%	–0.3%
	3	1.0%	0.3%	–0.1%	–0.5%	–1.8%	–0.2%
	4	1.0%	0.5%	0.1%	–0.7%	–2.6%	–0.4%
	5-high	0.6%	0.3%	–0.3%	–1.4%	–3.8%	–0.9%
	5-1	0.2%	0.1%	–0.3%	–1.1%	–2.4%	–0.7%
	t-stat.	0.5	0.4	–1.1	–4.0	–7.3	–2.7
		1-low	2	3	4	5-high	all
IVOL-3F	1-low	0.5%	0.2%	0.0%	–0.3%	–1.4%	–0.2%
	2	0.8%	0.3%	–0.1%	–0.3%	–1.6%	–0.2%
	3	1.0%	0.5%	–0.1%	–0.4%	–1.9%	–0.2%
	4	0.9%	0.4%	–0.1%	–0.7%	–2.6%	–0.4%
	5-high	0.5%	0.4%	–0.5%	–1.4%	–3.9%	–1.0%
	5-1	0.0%	0.2%	–0.6%	–1.1%	–2.5%	–0.8%
	t-stat.	0.1	0.6	–2.3	–4.2	–8.5	–3.5
		1-low	2	3	4	5-high	all
SVOL-3F	1-low	0.4%	0.2%	–0.1%	–0.4%	–1.9%	–0.4%
	2	0.5%	0.2%	–0.2%	–0.4%	–2.1%	–0.4%
	3	0.8%	0.2%	0.0%	–0.5%	–2.1%	–0.3%
	4	1.0%	0.4%	–0.1%	–0.7%	–2.3%	–0.3%
	5-high	0.9%	0.4%	0.1%	–0.8%	–3.1%	–0.5%
	5-1	0.5%	0.2%	0.1%	–0.4%	–1.2%	–0.2%
	t-stat.	1.8	0.7	0.5	–1.3	–4.2	–0.6

Note: This table shows average delta-hedged options returns of portfolios sorted by stock volatility and expensiveness (IV−HV). Panel A shows the results for calls and Panel B the results for puts. For each month of the data period January 1996 to August 2015, delta-hedged option returns are sorted by volatility (either VOL, IVOL-3F or SVOL-3F). Within each volatility quintile, option returns are then sorted by expensiveness. The table reports the average delta-hedged returns for each volatility-expensiveness combination, averaged over time. The last column (all) provides averages over all expensiveness categories. The row denoted by 5-1 presents the results for a long–short trading strategy that buys the portfolios with the highest volatilities (5-high) and sells the portfolios with the lowest volatilities (1-low). The t-statistics for the average returns of these portfolios are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation of the portfolio returns.

Table 4: Regressions of Average Returns of Long–Short (1-5) Portfolios When Expensiveness is High (5-high) on Different Combinations of Factors

Panel A: Calls

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Alpha	3.75%	3.74%	3.96%	3.74%	3.84 %
	(8.85)	(10.49)	(11.99)	(10.53)	(8.98)
MKT	0.255				0.063
	(3.52)				(0.51)
SMB	0.145				0.046
	(1.05)				(0.34)
HML	–0.281				–0.214
	(–2.69)				(–2.25)
MOM	–0.014				0.023
	(–0.15)				(0.26)
LowVol	4.362				–3.522
	(0.48)				(–0.39)
ZB-STR		–0.252		–1.847	–1.420
Index		(–4.00)		(–1.69)	(–1.30)
dVIX			–0.263		–0.110
			(–4.90)		(–1.23)
ZB-STR				–1.836	–0.685
Stocks				(–0.85)	(–0.26)
R^2_{adj}	0.115	0.088	0.104	0.088	0.162

Panel B: Puts

	Model 1	Model 2	Model 3	Model 4	Model 5
Alpha	2.54%	2.57%	2.63%	2.57%	2.56%
	(7.37)	(7.81)	(8.77)	(7.82)	(7.48)
MKT	0.158				0.113
	(2.25)				(1.14)
SMB	0.096				0.100
	(1.01)				(1.01)
HML	–0.217				–0.209
	(–3.14)				(–3.18)
MOM	–0.007				–0.013
	(–0.12)				(–0.21)
LowVol	0.629				0.441
	(0.09)				(0.06)
ZB-STR Index		–0.875		–1.354	–1.017
		(–1.63)		(–1.42)	(–1.17)
dVIX			–0.139		–0.053
			(–2.66)		(–0.77)
ZB-STR Stocks				1.310	2.305
				(0.69)	(1.07)
R^2_{adj}	0.120	0.016	0.049	0.014	0.120

Note: This table shows the results of different regression models that regress the returns of a low-volatility trading strategy on different combinations of factors. Panel A provides the results for calls and Panel B the results for puts. The low-volatility trading strategy holds long positions in a low-volatility portfolio (1-low) and short positions in a high-volatility portfolio (5-high). These portfolios refer to the highest expensiveness quintiles (see Table 2) and use IVOL-1F. Based on Fama and French's (1993) model, we consider the market factor (MKT), the value factor (HML) and the size factor (SMB). In addition, we use Carhart's (1997) momentum factor (MOM) and a low-volatility stock market factor (LowVol). Factors referring to the option market are the returns of zero-beta straddles on the S&P 500 Index (ZB-STR Index), the average returns of zero-beta straddles written on the component stocks of the S&P 500 Index (ZB-STR Stocks), and changes in the VIX Index (dVIX). The t-statistics (in parentheses) are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation.

Table 5: Average Returns and Alphas of Long–Short (1-5) Portfolios When Expensiveness is High (5-high) for Different Periods

Panel A: Calls

	Full Period	excl. Crisis	≤04/2003	>04/2003
Average Return	4.03%	4.05%	3.17%	4.54%
	(11.48)	(10.76)	(4.26)	(13.55)
Alpha	3.84%	3.74%	2.89%	4.60%
(Eight-Factor Model)	(8.98)	(7.09)	(3.60)	(12.09)

Panel B: Puts

	Full Period	excl. Crisis	≤04/2003	>04/2003
Average Return	2.67%	2.59%	1.38%	3.43%
	(8.91)	(7.74)	(2.37)	(14.11)
Alpha	2.56%	2.28%	1.02%	3.48%
(Eight-Factor Model)	(7.48)	(5.23)	(1.61)	(13.86)

Note: This table shows the average returns and alphas of a low-volatility trading strategy for different time periods. Panel A provides the results for calls and Panel B the results for puts. The low-volatility trading strategy holds a long position in a low-volatility portfolio (1-low) and a short position in a high-volatility portfolio (5-high). These portfolios refer to the highest expensiveness quintiles (see Table 2) and use IVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 4. The full data period is from January 1996 to August 2015. The crisis period is from June 2007 to December 2009. The t-statistics (in parentheses) are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation.

Table 6: Effect of Transaction Costs on Average Returns and Alphas of Long–Short (1-5) Portfolios When Expensiveness is High (5-high)

Panel A: Calls

ESRP/QSPR	MidP	10%	25%	50%
Average Return	4.03%	3.30%	2.22%	0.46%
	(11.48)	(9.88)	(6.81)	(1.29)
Alpha	3.84%	3.08%	1.96%	0.14%
(Eight-Factor-Model)	(8.98)	(7.42)	(4.80)	(0.34)

Panel B: Puts

ESRP/QSPR	MidP	10%	25%	50%
Average Return	2.67%	2.16%	1.39%	0.08%
	(8.91)	(7.49)	(4.98)	(0.28)
Alpha	2.56%	2.04%	1.24%	–0.10%
(Eight-Factor-Model)	(7.48)	(6.16)	(3.90)	(–0.33)

Note: This table shows the average returns and alphas of a low-volatility trading strategy for different levels of transaction costs. Panel A provides the results for calls and Panel B the results for puts. The low-volatility trading strategy holds long positions in a low-volatility portfolio (1-low) and short positions in a high-volatility portfolio (5-high). These portfolios refer to the highest expensiveness quintiles (see Table 2) and use IVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 4. The data period is from January 1996 to August 2015. The different transaction cost scenarios refer to different ratios of ESPR to QSPR: 10%, 25%, or 50%. As a reference point, the table also includes the case without transaction costs (MidP). The t-statistics (in parentheses) are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation.