On the Determinants of Premiums in Financial Markets

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Abstract

This dissertation analyzes the pricing, exposures as well as information content of options. It aims to fill research gaps in the existing options-literature in the research fields of volatility-related pricing, option-exposures as well as option-implied information. It consists of three main chapters each of which is based on an individual study.

The first study (Chapter 2), *A New Look at the Cross-Section of Option Returns and Volatility*, analyzes the relationship between the low-volatility effect and the expensiveness effect in stock options. Building on intermediary asset pricing theory, we hypothesise a linkage between the two volatility-related patterns that is based on market maker positions and market imperfections. The results show that the low-volatility effect is present in high-expensiveness options whereas the expensiveness effect increases with volatility. These findings cannot be explained by market inefficiencies or times of crisis. The study highlights the importance of market makers in options markets, the role of volatility in option pricing and offers benefits for investors as the effects cannot be explained by common risk factors.

The second study (Chapter 3), *Exposures of Delta-Hedged Option Portfolios*, analyzes the exposures of delta-hedged option portfolios to different risks and firm characteristics. The results show that these option portfolios have exposure to volatility, skewness, kurtosis as well as volatility and skewness uncertainty which are mainly driven by idiosyncratic risks. Further, delta-hedged option portfolios also have exposure to certain firm characteristics. An analysis of the triangular relationship between delta-hedged option returns, stock return moments and firm characteristics shows that the exposure to firm characteristics is especially informative when the stock return moments indicate low risk. This suggests that firm characteristics hold additional information about the riskiness of the underlying and can be interpreted as alternative risk measures.

The third study (Chapter 4), *A Tale of Two Crises Told by Options*, analyzes and compares the Global Financial Crisis and the COVID-19 pandemic using option-implied information. Because option prices contain information about the conditional expected return distribution of the underlying (the risk-neutral density), they are particularly suited for analyses of crises. Our results show both fundamental differences and important similarities of the two crises. Additionally, the use of risk-neutral densities allows us to

analyze reactions to significant events during each crisis and to ask whether the markets have entered a new regime after the systemic shock of the crises.

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1 Introduction

Options give the holder the right, but not the obligation, to buy or sell an underlying asset for a predetermined strike price at or until a predetermined date depending on whether it is a European or an American option (Hull, 2018). Although this definition is rather simple, it has important implications regarding the characteristics of options. The right to buy the underlying asset while not being obliged to do so leads to non-linearity of the payoff as the investor would not exercise an option unless it is profitable to do so. Hence, the payoff increases linearly with the price of the underlying starting from the predetermined strike price upwards for calls. Below the strike price, the payoff is simply zero. For puts, the payoff increases linearly with decreases of the underlying's stock price from the strike price downwards. Analogously, the payoff above the strike is zero. The determination of an expiration date leads to a finite time-to-maturity. Although other asset classes such as equities are forward-looking[1] as well, a specific expiration date allows market participants to use options with a time-to-maturity that best suits their needs. Lastly, the determination of a strike price allows market participants to use options for different expected return outcomes.

These features make options unique and eligible for many different use cases which ultimately serve three main purposes: i) trading, ii) risk management and iii) generation of information. Options allow investors to incorporate trading strategies that aim at profiting from more than just capital gains from stock price increases. The advantage of trading options over buying the underlying directly is their embedded leverage and the implicit bet on the underlying's volatility because of their non-linear payoff (Passarelli, 2012).[2]

[1] In the commonly known dividend discount model, the stock price equals the sum of all discounted future cashflows (Farrell, 1985). Because companies in this setting are assumed to have an infinite lifespan, stock prices are forward-looking with an infinite time-to-maturity.

[2] Option trading strategies are typically divided into volatility-buying and volatility-selling strategies. Popular examples of volatility-buying strategies, besides buying a naked option (i.e., without an investment in the

But options are not only useful for trading on non-linearities like volatility. They also serve as hedging instruments and are crucial for risk management and allocation. The sensitivities to changes of different price parameters such as the underlying's stock price are measured with the Greeks and are therefore particularly useful in risk management (Hull, 2018). The most commonly known hedging strategy is the delta hedge. Delta-hedged portfolios are immune to small changes in the underlying's asset value. This is achieved by a specific position in the underlying that counteracts the option position and is determined by the option's delta which measures the changes in option value caused by small changes in the underlying's stock price.[3] Because the underlying position value will counteract the option position, the delta hedge aims at constructing a portfolio with a delta of zero (delta-neutrality). In other words, the delta hedge cancels out the linear influence of the underlying (i.e., stock price movements).[4] However, as mentioned before, an important characteristic of options is their non-linearity. Hence, options also allow for hedging non-linear impacts of the underlying such as large price movements or changes in the volatility of the underlying.[5] Even without trading options or using them for risk management purposes, options have a useful property: they generate information. Options markets provide valuable information about the risk-neutral expectations of the underlying's future return distribution, the risk-neutral density (Breeden and Litzenberger, 1978; Figlewski, 2018). For financial regulators and investors, they provide a way to assess market conditions and sentiment. For monetary authorities, they additionally allow to assess the credibility and effectiveness of monetary actions. Further, they also help to explain abnormal price movements (e.g., a market crash or price jump). If investors price possible crash scenarios, the amount of news necessary to cause a sharp price drop might be less than in a scenario in which no crash scenario was priced. Hence, options and the derived risk-neutral densities help to explain market changes that are hard to be explained by news (Bahra, 2007).

underlying), are the straddle or the strangle where investors buy one call and one put on the same underlying with the same time-to-maturity and the same (straddle) or different (strangle) strike prices. Shorting these positions turns them into volatility-selling strategies (Passarelli, 2012).

[3]Because options are typically written on 100 stocks, it is usually easier to adjust the number of stocks to the number of options than vice versa.

[4]Note that a delta hedge is not static. Because the delta itself changes with price movements of the underlying, frequent rebalancing of the portfolio is required to maintain delta-neutrality.

[5]See Hull (2012) for an overview of hedging strategies for different types of risks.

Three different strands of literature relevant for each of the three purposes. For the trading of options, pricing studies are relevant. This strand of literature studies the determinants of option prices and returns mainly in the cross-section of different underlyings. An underlying question of these studies therefore is for which determinants investors are willing to pay a premium. Most studies analyse volatility-related determinants (e.g., Goyal and Saretto, 2009); Cao and Han (2013); Ruan (2020). Further determinants include stock return-related determinants (e.g., An et al., 2014)), higher physical moments (e.g., Bali and Murray, 2013), higher risk-neutral moments (e.g., Kim and Kim, 2016), and firm characteristics (e.g., Zhan et al., 2022). The strand of literature studying options in a risk management context can be divided into two substrands. Although risk managers can also benefit from the contributions of pricing studies, the literature most relevant includes studies which analyze the role of options in risk management (e.g., Moschini and Lapan, 1995; Ahn et al., 1999; Mahul, 2002) and studies concerned with the hedging practices of firms (e.g., Gay et al., 2002; Brown and Toft, 2002; Korn, 2010). Additionally, studies which analyse the factor structure option prices and expected returns in the cross-section are also relevant in this context (e.g., Christoffersen et al., 2018a; Horenstein et al., 2022). Lastly, there exists an extensive literature on the information content embedded in option prices. This strand of literature reaches from theoretical papers on how to exploit option-implied information (e.g., Breeden and Litzenberger, 1978; Bakshi et al., 2003; Figlewski, 2009) to empirical studies on what this information tells us about markets (e.g., Bahra, 2007; Jackwerth, 2020).

For this dissertation, both the studies on individual equity options and on index options are relevant. More specifically, for the pricing literature, the studies investigating volatility-related determinants are most relevant and especially the studies by Cao and Han (2013) and Goyal and Saretto (2009). Cao and Han (2013) study the low-volatility effect in stock options which is commonly known from other markets (Ang et al., 2006, 2009). It describes the pattern that assets with low historical idiosyncratic volatilities yield abnormally high returns. This effect exists also in the options market. Here, options on stocks with low historical idiosyncratic volatilities earn abnormally high returns. Cao and Han (2013) argue that this is due to higher arbitrage costs of high idiosyncratic volatility stocks for market makers who in turn increase the prices of options on those stocks which decreases the option returns. Goyal and Saretto (2009) also study volatility-related determinants of option returns. More specifically, they document a monotonic relationship between the difference of implied and historical volatility (known as expensiveness (Gârleanu et al., 2009)). That is, a classic long-short strategy that buys options with a low expensiveness and sells options with a high expensiveness earns economically and statistically significant returns which Goyal and Saretto (2009) argue, is an indication for volatility mispricing. As for the risk management purpose of options, the papers of Christoffersen et al. (2018a) and Horenstein et al. (2022) show evidence for the existence of a factor structure in option prices and expected returns. They also show that relatively few factors explain a substantial part of the cross-sectional variation. For option prices, the factors include the implied volatility level, skew[6], and term-structure (Christoffersen et al., 2018a). For option returns, Horenstein et al. (2022) find that characteristics such as firm size, idiosyncratic volatility and the expensiveness as well as a market variance risk factor explain a substantial part of the variation in the cross-section. Lastly, as for the information content, the studies exploiting information via risk-neutral densities (RND) derived from S&P 500 index options during the Global Financial Crisis (GFC) and the recent COVID-19 crisis are most relevant. Because RNDs measure market sentiment and assist in assessing monetary policy actions or in identifying anomalies, they are particularly interesting in times of crisis. As for the GFC, Birru and Figlewski (2012) show that RNDs are strongly left-skewed both in times of high and low volatility. However, the higher risk-neutral moments (skewness and kurtosis) went down in magnitude during the GFC resulting in more symmetrical and normal-looking RNDs. In this regard, Gagnon et al. (2016) show that risk-neutral volatility is more internationally cointegrated than risk-neutral skewness and kurtosis which indicates that the crash fear and tail risk are more locally driven. As for the COVID-19 crisis, we know that risk premiums embedded in option prices are positively correlated to the COVID-19 policy strictness and react to WHO announcements (Li et al., 2022). Additionally, although COVID-19 was already widely known at the beginning of 2020 and already considered a crisis, the first visible reactions in the financial markets appear in mid-February (Hanke et al., 2020; Jackwerth, 2020). On the peak of the crisis on 16 March 2020, markets priced in a 40 % chance of a crash under the risk-neutral measure and did not expect the markets to recover before December 2020 (Jackwerth, 2020).

[6] The volatility skew is defined as the implied volatility curve across different moneyness levels (Christoffersen et al., 2018a).

These findings initially give the impression of a deep knowledge about the volatility pricing in options, the applicability of options for risk management purposes, and the information content embedded in equity options. However, the evidence on different volatility-related determinants driving option prices and returns, the sparse evidence on exposures of option portfolios as well as the valuable information for times of crisis raise further research questions that have not yet been answered.

As for the volatility-related determinants of option prices and returns, we know that the idiosyncratic volatility as well as the expensiveness is priced in options (Cao and Han, 2013; Goyal and Saretto, 2009). Since both measures are volatility-related, it stands to reason that they are somehow connected. Hence, a question that arises is: What is the relationship between the low-volatility and the expensiveness effect and how are they connected? What are possible explanations for the relationship that causes the potential patterns? Can investors benefit from the knowledge about the relationship between the two effects? Further, because there is only sparse evidence on the factor structure of option prices and returns, one could ask: What risks and firm characteristics do options have exposure to? Is the exposure mainly driven by the idiosyncratic or the systematic risk part? Assuming there is exposure to risks as well as firm characteristics, what is the triangular relationship of option returns with risk measures and firm characteristics? Lastly, because RNDs allow for the assessment of market expectations and given their particular suitability for studying times of crisis, the question arises what we learn from them about the development of market expectations regarding the events during the recent COVID-19 crisis. What do we learn from them about the important events of the GFC? How does the COVID-19 crisis compare with the GFC, given that both crises were fundamentally different but also had important similarities (Spatt, 2020)? All these questions can be summarized into three main research questions:

(i) How and why are the low-volatility and the expensiveness effect related to each other and if and how can investors exploit this relationship?

(ii) What are the exposures of delta-hedged option portfolios[7] to different risks and their risk parts as well as to firm characteristics and how do these exposures interact?

[7]Delta-hedged option portfolio are particularly suited for this analysis because the linear influence of the underlying (i.e.,the stock price) is hedged away and only non-linearities remain. In other words, delta-hedged option returns are not simply driven by their underlying's return.

(iii) What do we learn from option-implied information about the expectation changes due to important events during the COVID-19 crisis and how does it compare with the GFC?

Providing answers to these questions is the main objective of this dissertation. Thereby, this dissertation contributes to the literature on both individual and index options and increases the knowledge about the pricing in the cross-section, the exposures of individual equity options and the information content of index options. The findings are relevant for researchers, practitioners active in asset pricing, asset management or risk management as well as regulatory authorities. Each of the three main chapters consists of a self-contained study that can be read individually, and these studies answer the aforementioned questions in turn. Chapter 2 deals with the question of the relation between the low-volatility effect and the expensiveness effect and with possible explanations. Further, it addresses if and how investors can benefit from the relationship between the two well-known anomalies. In Chapter 3, the exposures of delta-hedged options returns to different risks and firm characteristics are analysed and also how these exposures interact. Lastly, in Chapter 4, the information content of index options is addressed by comparing the GFC and the COVID-19 crisis regarding the development of market expectations throughout the respective crisis. The three studies are summarized in the following.

The first study (Chapter 2), *A New Look at the Cross-Section of Option Returns and Volatility*[8], analyses the relationship between the low-volatility effect and the expensiveness effect in stock options. Not only are both effects volatility-related, but also the recent developments in the intermediary asset pricing literature suggest a linkage between the two effects. Financial intermediaries, or market makers, are crucial for price setting in the options market (He and Krishnamurthy, 2013; He et al., 2017; Kargar, 2021). The expensiveness may contain valuable information about the net position of market makers because of its correlation with option demand (Bollen and Whaley, 2004; Gârleanu et al., 2009; Fournier and Jacobs, 2020). Because holding a short position in options is significantly more risky than holding a long position, if market makers are net long, there are price discount and expected returns are high whereas if market makers are net short, there are price premiums and expected returns are low to offset market maker costs and

[8]This study is joint work with Olaf Korn and David Volkmann.

risks (Bollen and Whaley, 2004; Gârleanu et al., 2009; Muravyev, 2016; Kanne et al., 2023). Hence, the higher the net-demand of investors for options, the higher the expensiveness of options on average. Moreover, volatility, especially the idiosyncratic volatility, poses as a proxy for market imperfections as stochastic volatility is a non-hedgeable risk for market makers which leads to inventory risk and therefore affects option prices and returns (Gârleanu et al., 2009). The variance risk is positively correlated with volatility which is in line with standard option pricing models (Heston, 1993; Christoffersen et al., 2018a) as well as with findings of empirical studies (e.g., Baltussen et al., 2018). Additionally, there is also evidence that volatility is positively correlated with the illiquidity of a stock (Comerton-Forde et al., 2010). Hence, market imperfections increase with volatility. Taken together, the net position of market makers should affect the implications of market imperfections for market makers (and vice versa), leading to a linkage between the low-volatility and the expensiveness effect.

To study the relationship between the two effects, we calculate double sorts of delta-hedged option returns using a dataset of all US-listed equity options from January 1996 to June 2021. The advantage of double sorts is that they give a detailed picture of the interaction between effects without imposing a parametric form (Fritzsch et al., 2021). Additionally, our data sample allows for an explicit analysis of the structural change of options markets in 2003[9] as well as times of crisis such as the GFC and the COVID-19 crisis. It is well-known that returns of volatility-strategies are quite sensitive to outliers during turbulent market times (Kozhan et al., 2013). Hence, we analyse crisis periods to shed more light on the question whether option returns are (in-part) a compensation for rare catastrophes (Barro, 2006, 2009). Lastly, we analyse if and how investors can exploit the relationship and profitably trade on it.

The empirical results show a clear relationship between the low-volatility effect and the expensiveness effect: The low-volatility effect is present only in options where the expensiveness is high, and the magnitude of the expensiveness effect grows monotonically with volatility. Further, we show that our results are neither driven by inefficiencies nor by outliers in times of crisis. Regarding the profitability of these patterns, we find that only investors with low transaction costs are able to profitably trade on them.

[9]In April 2003, the Securities and Exchange Commission's (SEC's) market linkage plan became effective.

The second study (Chapter 3), *Exposures of Delta-Hedged Option Portfolios*, focuses on the exposures of delta-hedged option returns to different risks and firm characteristics that are inspired by well known pricing anomalies. There is ample evidence on the pricing of risk-related determinants of option prices. Especially for the moments of the return distribution, we know that volatility, skewness as well as kurtosis are priced in delta-hedged option returns (e.g., Cao and Han, 2013; Kim and Kim, 2016). However, little is known about the exposures of delta-hedged option portfolios to these risks. While pricing studies suggest determinants that delta-hedged option portfolios should have exposure to, there is no explicit analysis of delta-hedged option exposures. Hence, in this study, I analyse the exposure of delta-hedged option returns to the aforementioned risks and firm characteristics and their interaction with one another.

I analyse these exposures with fixed-effects regressions using year fixed effects and a dataset of all US-listed equity options from January 1996 to June 2021. Because the moments of the return distributions are highly correlated, I orthogonalize all moments to isolate the effect of the respective moment. To distinguish between the idiosyncratic and the systematic risk part, I use the market model because I argue that it is most suitable in this setting. For the calculation of the vol-of-vol, I follow the methodology of Baltussen et al. (2018) to ensure a decoupling from the volatility and the variance risk. Further, the selection of firm characteristics is inspired by the study of Zhan et al. (2022) who analyse the pricing of firm characteristics known from pricing anomalies in the stock market. Lastly, I also analyse the triangular relationship between delta-hedged option returns, the moments of the underlying's return distribution and firm characteristics using double sorts for a detailed breakdown of the triangular relationship.

The results show that delta-hedged option returns have highly significant exposures to all moments in the expected direction. That is, delta-hedged option portfolios have positive exposure to the even moments (i.e., volatility and kurtosis) and negative exposure to skewness. In other words, options serve as an insurance against volatility and kurtosis increases as well as skewness decreases which is compatible with known investor preferences (e.g., Dittmar, 2002; Litzenberger and Kraus, 2016). Interestingly, these exposures are mainly driven by idiosyncratic risks. Delta-hedged option returns also have positive exposure to variance risk and skewness risk which are also mainly driven by their idiosyncratic risk parts. Interestingly, to the systematic risk parts, delta-hedged option return have negative exposure. Regarding the firm characteristics, delta-hedged option portfolios have exposure to most but not all firm characteristics, namely to the cash-to-assets ratio, the logarithmic stock price, the profitability, the profit margin, the share issuance over the last year as well as the Z-score which measures default risk. Of these exposures, some are consistent with findings of other studies while some remain puzzling. The analysis of the interaction between delta-hedged option returns, idiosyncratic moments and firm characteristics shows that firm characteristics are most informative when the moments indicate low risk which might be an indication of a peso problem and suggests that firm characteristics may be interpreted as alternative risk measures.

The third study (Chapter 4), *A Tale of Two Crises Told by Options*[10], is concerned with the information content embedded in S&P 500 index options and a comparison of the GFC with the COVID-19 crisis. Although these crises are fundamentally different because the GFC is a crisis caused by the financial system itself and the COVID-19 crisis is a crisis that originated in the health sector, these crises also have important similarities such as the importance of financial injections into the markets (Spatt, 2020). To analyse the development of market expectations, option-implied information is particularly valuable. Options are by nature forward-looking which abstracts from the hindsight bias, have a finite time-to-maturity which allows for the analysis of different time horizons, and because of the different strike prices, they allow for investigations of the expectations for different return outcomes. A way to study the whole spectrum of expectations over one time horizon is by deriving RNDs from option prices. The time series of RNDs and risk-neutral skewness give a detailed picture about the developments of market expectation throughout the crises and especially at important events during the crises. Because we are able to analyse two crises, we aim to shed more light on the development of market expectations in times of crisis and are able to highlight important similarities and differences of the crises.

As mentioned above, RNDs are particularly well suited to investigate market expectations. The only disadvantage is that they can only be calculated for a certain time-to-maturity at any point in time. This makes it rather difficult to highlight the development of market expectations. One way to convert the information embedded in RNDs into a

[10]This study is joint work with Olaf Korn.

time-series is to calculate the time-series of different quantiles of daily RNDs. This allows to show the market expectations for different return outcomes as well as their development throughout the crises. Since important events during a severe crisis can greatly change the shape of RNDs, we analyze the complete RNDs on significant days to show their shapes. Lastly, another advantage of RNDs is the incorporation of investors' risk-aversion. Because risk-neutral skewness indicates risk-aversion (Bakshi et al., 2003), we calculate the time-series of this metric as well to show the development of risk-aversion during both crises.

The comparison between the two crises show fundamental differences but also important similarities. The most striking commonality is that although the respective crisis has already begun, it still takes some time until investors shift their expectations towards a significant crisis scenario. Additionally, both crises indicate heightened risk-aversion after the shock compared to before. But there are also important differences between the crises. Although it takes some time until investors price significant crash scenarios during both crises, this takes significantly longer during the GFC than during the COVID-19 crisis. While the COVID-19 crisis begins at the beginning of 2020, the first visible reactions in the financial markets appear in mid-February 2020 and the crisis reaches its peak mid-March 2020 before subsiding. During the GFC which began in June 2007, market expectations regarding a potential crash scenario vary widely. The first market reactions towards a crash scenario are shown in February 2008. The weight of the priced crash scenario in the risk-neutral densities increases until the bailout of Bear Stearns in March 2008 before declining again. Only the bankruptcy of Lehman Brothers leads to a notable pricing of a crash scenario although at first, investors do not seem to be able to classify this event. However, this bankruptcy marks the starting point of a deep crisis that reaches its peak in mid-November 2008 before subsiding again. The risk-neutral skewness is lower in both crises after the shock than before, which illustrates the increased risk-aversion. However, for the COVID-19 crisis, the risk-neutral skewness shows a downward-sloping trend until the end of the sample. As for the GFC, the risk-neutral skewness tends to shift downwards after the shock and the market seems to be entering a new regime with persistently elevated risk-aversion.

The findings in this dissertation are relevant for researchers, practitioners who are working in asset pricing, asset management or risk management as well as for monetary authorities.

For researchers, the papers contribute important insights into the pricing of equity options in the cross-section, add to the literature on intermediary asset pricing as well as to the literature studying the low-volatility effect. Additionally, it provides the first exposure analysis of delta-hedged option returns in the cross-section and shows important similarities and differences of the GFC and the COVID-19 crisis which adds to both the strand of literature analysing crises as well as to the body of literature using option-implied information in different settings. But also practitioners such as portfolio managers, risk managers or regulatory authorities can gain valuable insights into the different purposes of options. The findings from Chapter 2 benefit portfolio managers and institutional investors with low transaction costs who are therefore able to profitably exploit the relationship between the low-volatility and the expensiveness effect. But also investors with higher transaction costs can benefit from the results. Since both effects are likely to persist over time, they should be considered by investors. Chapter 3 is particularly interesting for risk managers who use options in their hedging strategies and therefore need to know which exposures options have to use them appropriately in their risk management strategies. Lastly, Chapter 4 benefits investors who seek to use option-implied information to assess current market conditions and sentiment as well as regulatory authorities who use option-implied information for anomaly identification and in the assessment of policy actions.

2 A New Look at the Cross-Section of Option Returns and Volatility

Joint work with Olaf Korn and David Volkmann.

Abstract

This paper re-examines two volatility-related patterns in the cross-section of stock option returns: the low-volatility effect and the expensiveness effect. Intermediary asset pricing theory suggests specific linkages between these effects. As our empirical results show, the low-volatility effect is primarily present for expensive options and the expensiveness effect increases with volatility. In this way, the paper provides new evidence on the role of volatility in the economics of options markets and on the importance of intermediaries and market imperfections. Our results offer potential benefits for investors, as the conditional effects cannot be explained by common risk factors or market inefficiencies.

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2.1 Introduction

Options markets play a crucial role for the allocation and management of risks. Developing a better understanding of how they work is therefore an important task in financial economics. Because options have non-linear payoffs, option prices and returns are naturally linked to the return volatility of the underlying. In this paper, we re-examine two volatility-related patterns in the cross-section of stock option returns. Based on intermediary asset pricing theory, we hypothesize specific linkages between these volatility-related patterns and investigate them in an empirical study. In this way, the paper provides new evidence on the role of volatility in the economics of options markets. This new evidence also offers potential benefits for investors.

The first return pattern that we reconsider has been documented by Cao and Han (2013): delta-hedged option returns decrease with an increasing idiosyncratic volatility of the underlying stock. We call this pattern the low-volatility effect, in analogy to similar effects that have been observed in other financial markets (Ang et al., 2006, 2009; Duan et al., 2010). The second return pattern is that delta-hedged option returns decrease with the "expensiveness" of an option, defined as the difference between the option's implied volatility and a historical benchmark volatility (Goyal and Saretto, 2009). Following the terminology in Gârleanu et al. (2009), we call this pattern the expensiveness effect.

Our re-examination of the low-volatility and expensiveness effects is motivated by the recent theoretical and empirical literature on intermediary asset pricing. There is evidence that intermediaries play a crucial role in price determination, particularly in option markets, where trading is executed via specialized intermediaries, the market makers (He and Krishnamurthy, 2013; He et al., 2017; Kargar, 2021). Based on an economic rationale derived from intermediary asset pricing theory, we hypothesize a close linkage between the low-volatility and expensiveness effects. In particular, we suggest that the low-volatility effect is driven by options with high expensiveness only and the expensiveness effect is stronger for options written on high-volatility stocks.

A further reason for our re-examination of the expensiveness and low-volatility effects is the large market movements in stock and options markets during the COVID-19 pandemic. As variance-related trading strategies are known to be very sensitive to extreme events (Kozhan et al., 2013), crisis periods help to understand if positive mean returns in normal times are merely a compensation for rare disasters (Barro, 2006, 2009). Because our data set contains two crisis periods, the Global Financial Crisis (GFC) and the COVID-19 pandemic, our study provides new evidence on this issue. Moreover, a longer data period, as compared to previous investigations, might reveal if improved market efficiency had an impact on volatility-related return patterns.

Our empirical results provide clear support for our hypotheses about the linkage between low-volatility and expensiveness effects. An inverse relation between stock volatility and future option returns holds only for options with high expensiveness. No such relation exists if expensiveness is low. We also find the magnitude of the expensiveness effect to grow significantly with stock return volatility. There is no evidence, however, that these effects are due to risk premiums for rare disasters or just reflect inefficiencies in options markets that have ceased over time.

The results of our paper contribute to a better economic understanding of the low-volatility and expensiveness effects in the cross-section of option returns by providing new evidence on their interconnectedness. The kind of observed interconnectedness is in line with an economic setting where market makers act under varying market imperfections and expensiveness and return volatility contain information about market makers' net positions and the severity of imperfections, respectively. If investors want to integrate the low-volatility or expensiveness effects into their option trading strategy, they could use the other effect as conditioning information. Such conditional effects are about two to three times stronger than the unconditional ones. Because the conditioning variables that we use in our study require knowledge of historical stock and option prices only, the necessary information is relatively easy to obtain.

Our paper contributes to three strands of literature. First, it belongs to the empirical literature on intermediary asset pricing. Theoretical and empirical work has documented the important role of intermediaries for price formation in financial markets (Perotti and Rindi, 2010; He et al., 2017; Haddad and Muir, 2021) and in particular options markets (Muravyev, 2016; Fournier and Jacobs, 2020). The results of our paper show that intermediary asset pricing could also contribute to a better understanding of the expensiveness effect. In their seminal paper, Goyal and Saretto (2009) find the expensiveness effect to be in line with empirical predictions of the behavioral model of Barberis and Huang (2001). Our paper complements these results by hypothesizing and testing an empirical relation between expensiveness and historical volatility that fits well into the framework of intermediary asset pricing.

Second, our paper 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, 2021), or speculative demand due to investor preferences for lottery-like payoffs (Bali et al., 2011, 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.[11] 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 because market makers would increase the prices of options on high-volatility stocks (to meet the higher costs), leading to decreasing returns. 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.

Third, 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 and the expensiveness effect—are closely related. Our paper also complements other results on specific regularities in option returns by stressing the potential importance of conditioning on market-maker positions (Kanne et al., 2023) and the general importance of market imperfections for the understanding of the cross-section of expected option returns (Christoffersen et al., 2018b; Hitzemann et al., 2021).

Our paper is structured as follows: In Section 2.2, we introduce the conditional low-volatility and expensiveness effects and develop hypotheses for our empirical investigation. Section 2.3 describes our data set and the data processing. Next, we present our main results on the conditional low-volatility and expensiveness effects in Section 2.4. In

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

Section 2.5, we provide additional results, centering on the extent to which the effects are beneficial for investors. Section 2.6 concludes.

2.2 Conditional Low-Volatility and Expensiveness Effects: Economic Rationales

This paper takes a new look at the low-volatility and expensiveness effects in options markets. In particular, it investigates the potential linkage between the two effects. An economic rationale for such a linkage is based on intermediary asset pricing theory and market imperfections. The main idea states that option expensiveness may provide useful information about the net position of market makers in a particular option series and stock return volatility may contain useful information about the severity of market imperfections related to this option.

There is both theoretical and empirical evidence that the signs of premiums in option markets depend on the sign of the net demand market makers face: if end users are net sellers and market makers are required to hold a net long position in an option series, there are price discounts and expected option returns are high. If market makers hold net short positions, however, there are price premiums and expected returns are low to provide a compensation for the costs and risks market makers are facing (Bollen and Whaley, 2004; Gârleanu et al., 2009; Muravyev, 2016; Fournier and Jacobs, 2020; Kanne et al., 2023). Therefore, the sign of the net position of market makers is important information for the understanding of option returns. Expensiveness may serve as a simple and easily observable proxy for such information. As shown by Bollen and Whaley (2004), Gârleanu et al. (2009), and Fournier and Jacobs (2020), there is a positive relation between demand and expensiveness. The higher the net end-user options demand for long positions in options, the more expensive an option is on average.

The level of stock return volatility may also provide useful information within an intermediary asset pricing framework. It may serve as a simple proxy for the magnitude of market imperfections affecting the corresponding option market. One argument states that stochastic volatility is an important non-hedgeable risk for market makers, and volatility risk increases with the volatility level. Such a relation is in line with standard option pricing models. For example, in the model by Heston (1993), variance risk is proportional to volatility. In the model by Christoffersen et al. (2018a), both market variance risk and idiosyncratic variance risk are proportional to market volatility and idiosyncratic volatility, respectively. Moreover, Baltussen et al. (2018) provide empirical evidence for a positive relation between stock return volatility and the vol-of-vol. Non-hedgeable risks, like volatility risk, lead to inventory risk of market makers, and inventory risk can have significant effects on option prices and returns (Gârleanu et al., 2009). Another argument that supports the view of volatility proxying market imperfections is that stocks with higher return volatility tend to be more illiquid (Comerton-Forde et al., 2010), leading to higher hedging costs of market makers in the corresponding option market. There is also empirical evidence that high-volatility stocks are more difficult to borrow than low-volatility stocks (Goyenko and Schultz, 2021), leading to problems if market maker positions require short sales for hedging. Irrespective of the specific kind of market imperfection, volatility could be a useful proxy for the magnitude of market imperfections.

If expensiveness is indicative for the sign of the net position of market makers and volatility is indicative for the severity of market imperfections that market makers face, we can hypothesize a first linkage between expensiveness and low-volatility effects. With market makers holding net short positions in options, more severe market imperfections lead to higher option prices and lower returns. Therefore, option returns should decrease with stock volatility if expensiveness is high, i.e., there is a low-volatility effect. If market makers are net long and expensiveness is low, however, higher stock volatility could even be associated with higher option returns. This argument leads to our first hypothesis.

Hypothesis 1: *The low-volatility effect is stronger for options with high expensiveness than for options with low expensiveness.*

Hypothesis 1 states that expensiveness contains important conditioning information with respect to the low-volatility effect, i.e., the conditional low-volatility effect differs from the unconditional one. The framework of intermediary asset pricing, however, does also offer a rationale for a conditional expensiveness effect, with volatility as the conditioning variable. If expensiveness provides useful information on the net position of market makers, the expensiveness effect reflects, at least partly, the return difference between long- and short positions of market makers. If this return difference contains a compensation for the risks and costs that market makers have to deal with, it should increase with the magnitude of market frictions, i.e. with the level of return volatility. This argument leads to our second hypothesis.

Hypothesis 2: *The expensiveness effect is stronger for options written on stocks with high volatility than for options written on stocks with low volatility.*

Hypotheses 1 and 2 take the perspective that market imperfections are at the heart of the low-volatility and expensiveness effects. Even if these hypotheses were supported empirically, potential alternative explanations for the conditional low-volatility and conditional expensiveness effects are still to 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.[12] In particular, as our data period includes two crisis periods, the GFC and the COVID-19 pandemic, our re-examination can offer new evidence on whether the low-volatility and expensiveness premiums are just a compensation for the risk of extreme events that severely affect option-based trading strategies. Second, it is an important question whether the conditional low-volatility and expensiveness effects are big enough to offer significant trading profits even after accounting for transaction costs. If the answer is yes, then at least part of the effects could be a result of market inefficiencies. The question if such market inefficiencies still exist or were reduced over time is another important piece of information for investors. The extended data period of our study offers new evidence on this issue too.

2.3 Data and Data Processing

2.3.1 Data Sources and Filters

Our 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,

[12]Natter et al. (2016) show that mutual funds do use options successfully. Equity funds' option use leads to a better risk-adjusted performance.

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. Moreover, we also obtain stock returns for the options' underlyings from the IvyDB database to calculate historical 30-day stock volatilities.[13] The sample period for the options and stock return data is from January 1996 to June 2021.

We use similar data filters as in previous studies (e.g., Goyal and Saretto, 2009; Cao and Han, 2013; Kanne et al., 2023) 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 to retain an observation in our sample.

Furthermore, we use Kenneth French's database to obtain the returns of specific factor portfolios. Risk-free interest rates are also taken from Kenneth French's database.

2.3.2 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 in the same way as Cao and Han (2013). Consider one call (put) option that is dynamically delta-hedged with the underlying stock and a risk-free bond over the period from time t to time $t + \tau$. The hedge is discretely rebalanced N times at dates t_n,

[13]Stock data is usually obtained from the Center for Research in Security Prices (CRSP) database (e.g., Cao and Han, 2013; Zhan et al., 2022). However, the process of matching the options data from IvyDB with stock return data from CRSP results in a loss of observations. To avoid this loss of observations, we decided to obtain the stock return data from IvyDB as well. Some preliminary analysis of stock return data that is available both in CRSP and IvyDB shows virtually no differences between returns.

$n = 0, \dots N-1$, where t (t_0) refers to the day when we set up the delta-hedged option position (end of month) and $t+\tau$ (t_N) is the last trading day of the option. Delta-hedged option returns are calculated as

$$R^C_{t,t+\tau} = \frac{C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta^C_{t_n} \left[S_{t_{n+1}} - S_{t_n} \right] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left[C_{t_n} - \Delta^C_{t_n} S_{t_n} \right]}{Abs(C_t - \Delta^C_t S_t)}, \quad (2.1)$$

$$R^P_{t,t+\tau} = \frac{P_{t+\tau} - P_t - \sum_{n=0}^{N-1} \Delta^P_{t_n} \left[S_{t_{n+1}} - S_{t_n} \right] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left[P_{t_n} - \Delta^P_{t_n} S_{t_n} \right]}{Abs(P_t - \Delta^P_t S_t)}, \quad (2.2)$$

where S represents the price of the underlying stock at the respective dates, C and P the closing mid prices of calls and puts, respectively, and Δ^C and Δ^P the options' deltas. a_n is the number of calendar days between dates t_n and t_{n+1} and r_{t_n} denotes the annualized risk-free rate on date t_n. The numerators in Equations (2.1) and (2.2) provide the dollar gains (losses) of the three portfolio components: options, stocks and bonds. To make these gains comparable between different stocks, they are scaled by the initial absolute value of the positions in options and stocks, as in Cao and Han (2013).[14] With this scaling, the returns $R^C_{t,t+\tau}$ and $R^P_{t,t+\tau}$ can be interpreted as the excess returns over the risk-free rate of a portfolio of one option minus delta stocks.

Given our data period and the data filters, we have 508,487 delta-hedged call returns and 506,874 delta-hedged put returns. As the data period covers 306 months, we have on average 1,662 calls and 1,656 puts in a cross-section. However, the number of observations per cross-section increases over time. Panels A and B of Table 2.1 provide summary statistics of the delta-hedged call and put returns as well as selected options' characteristics. Average delta-hedged returns are negative for both calls and puts and show a large dispersion. The return period (time-to-maturity of options) is, on average, close to 49 days and the moneyness of the options is close to one. In the latter part of our paper, we use different

[14] Because the initial value of the portfolio of options, stocks and bonds is zero, we cannot use this value as the denominator of Equations (2.1) and (2.2). Alternatively, we could use the stock price or the option price. For comparison reasons, we stick with the scaling used in Cao and Han (2013).

Table 2.1: Summary Statistics for Options and Volatilities.

Panel A: Call Options (508,487 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.9%	9.5%	–7.4%	–3.8%	1.6%	5.8%
Days to Maturity	48.8	4.1	46.0	49.0	51.0	52.0
Moneyness (S/K)	1.00	0.05	0.93	0.97	1.03	1.06
Option Spread	30.9%	33.6%	6.2%	10.5%	36.7%	73.9%

Panel B: Put Options (506,847 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.9%	7.9%	–6.7%	–3.4%	1.2%	4.7%
Days to Maturity	48.8	4.1	46.0	49.0	51.0	52.0
Moneyness (K/S)	1.00	0.05	0.94	0.97	1.03	1.06
Option Spread	30.8%	33.5%	6.3%	10.5%	36.4%	73.2%

Panel C: Volatility Measures

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
VOL	46.2%	32.6%	18.7%	26.0%	56.9%	82.1%
IdioVOL-1F	39.6%	29.8%	14.8%	21.2%	49.3%	71.8%
IdioVOL-3F	36.1%	27.7%	13.4%	19.2%	45.0%	65.9%
IV−HV	–0.3%	17.9%	−16.3%	–6.6%	5.9%	14.5%

Note: This table shows summary statistics of the options and volatility data that we use in our empirical study. 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 ($q_{0.9}$)) of the respective variables. The data period is January 1996 to June 2021. Panel A shows summary statistics for call options: delta-hedged option returns, days to maturity, moneyness, and option spreads. Delta-hedged returns are calculated as given in Equation (2.1). Moneyness is defined as the ratio of strike price (K) to spot price (S). Option spreads are quoted spreads at the beginning of the return period, measured in percent of the mid price. Panel B shows the corresponding summary statistics for put options. Delta-hedged put returns are calculated according to Equation (2.2). Panel C provides summary statistics for different volatility measures. The first three measures refer to annualized historical volatilities, estimated from daily returns over a 30-day data window. We distinguish between total volatility (VOL), idiosyncratic volatility according to a market model (IdioVOL-1F) and idiosyncratic volatility according to the three-factor model by Fama and French (1993) (IdioVOL-3F). The fourth measure, IV−HV, is the difference between two volatilities. IV denotes the implied volatility of the options and HV is a historical 365-day benchmark volatility.

transaction cost scenarios. The core element of these scenarios is the option's quoted spread. Therefore, summary statistics of quoted spreads are also included in Panels A and B of Table 2.1.

2.3.3 Volatility Measures

To investigate the cross-sectional relation between option returns and stock volatilities, we need to calculate volatilities, closely following 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.[15] This is our measure of total volatility (VOL). To separate VOL from idiosyncratic volatility, we use either the market factor or the three-factor model by Fama and French (1993).[16] The corresponding idiosyncratic volatilities are denominated as IdioVOL-1F and IdioVOL-3F, respectively. Panel C of Table 2.1 shows summary statistics of the (annualized) volatilities that we use in our study.

To study the connection between low-volatility effect and expensiveness effect, we need to measure expensiveness. Expensiveness is the difference between two volatilities: the option's implied volatility (IV) and a benchmark volatility estimate from historical stock-return data (HV). Our implementation of IV-HV uses the date t IVs of the call and put options from OptionMetrics. For the HV benchmark, we employ the 365-day volatility for the period preceding date t, as in Goyal and Saretto (2009). Summary statistics of IV-HV are also shown in Panel C of Table 2.1.

2.4 Conditional Low-Volatility and Expensiveness Effects: Empirical Evidence

As a reference point for our analysis, we look at the unconditional low-volatility and expensiveness effects. We quantify these effects via single sorts. 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 or expensiveness measure (IV−HV). As volatility measures, we use either VOL, IdioVOL-1F, or IdioVOL-3F. For each quintile portfolio and each month, we calculate the average portfolio return, using equal weights for all individual options. Finally, we calculate the (time series) average return of each quintile portfolio. Table 2.2 provides the results of these calculations. Panel A presents the results for call options and Panel B the corresponding results for put options. The columns 1-low refer to portfolios in the lowest volatility or expensiveness quintiles, and the columns 5-high to the highest volatility or expensiveness quintiles. Columns 1-5 provide the average returns of portfolios that takes a long position in the 1-low portfolio and a short positions in the 5-high portfolio. The returns of theses long-short tradings strategies

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

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

show in how far options on low-volatility stocks outperform options on high-volatility stocks and in how far cheap options outperform expensive options.

Table 2.2: Unconditional Low-Volatility and Expensiveness Effects.

Panel A: Delta-hedged call returns				
	Low-Volatility Effect			Expensiveness Effect
	VOL	IdioVOL-1F	IdioVOL-3F	IV-HV
1-low	-0.4%	-0.3%	-0.3%	0.4%
2	-0.5%	-0.4%	-0.4%	0.1%
3	-0.6%	-0.6%	-0.5%	-0.2%
4	-0.9%	-0.9%	-1.0%	-0.7%
5-high	-1.8%	-1.9%	-2.0%	-3.8%
1-5	1.4%	1.6%	1.7%	4.2%
t-stat.	5.8	7.2	7.4	16.3
Panel B: Delta-hedged put returns				
	VOL	IdioVOL-1F	IdioVOL-3F	IV-HV
1-low	-0.5%	-0.5%	-0.4%	0.1%
2	-0.6%	-0.5%	-0.5%	-0.1%
3	-0.6%	-0.6%	-0.6%	-0.3%
4	-0.9%	-0.9%	-0.9%	-0.8%
5-high	-1.6%	-1.8%	-1.8%	-3.2%
1-5	1.1%	1.3%	1.4%	3.3%
t-stat.	6.5	8.4	8.8	19.2

Note: This table shows average delta-hedged option returns of portfolios obtained via single sorts either by stock return volatility or expensiveness (IV−HV). Panel A provides the results for calls and Panel B the results for puts. For each month of the data period January 1996 to June 2021, delta-hedged option returns are sorted by volatility (either VOL, IdioVOL-1F or IdioVOL-3F) or expensiveness and grouped into volatility or expensiveness quintiles. The table reports the average delta-hedged returns for each quintile portfolio, averaged over time. The row denoted by 1-5 presents the results for a long–short trading strategy that buys the portfolio with the lowest volatility or expensiveness (1-low) and sells the portfolio with the highest volatility or expensiveness (5-high). 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.

As the results in Table 2.2 show, significant low-volatility and expensiveness effects exist for both calls and puts. Quantitatively, the effects are slightly stronger for calls. Moreover, the average returns of the 1-5 volatility portfolios are slightly higher for idiosyncratic volatility (IdioVOL-1F and IdioVOL-3F) than for total volatility (VOL). This is in line with the rationale that idiosyncratic volatility is a more challenging problem for market makers, as hedging instruments like VIX futures do exist for market volatility but usually not for idiosyncratic volatility. Another observation is that the unconditional expensiveness effect is stronger than the unconditional low-volatility effect. The 49-day return of a long-short expensiveness strategy delivers 4.2% an average for calls, whereas a long-short low-volatility strategy delivers at most 1.7%.

Table 2.3: Conditional Low-Volatility and Expensiveness Effects.

Panel A: Delta-hedged call returns

		Option Expensiveness (IV−HV)						
VOL		1-low	2	3	4	5-high	1-5	t-stat.
	1-low	0.4%	0.1%	-0.1%	-0.5%	-1.8%	2.2%	14.5
	2	0.5%	0.2%	-0.2%	-0.5%	-2.4%	3.0%	14.9
	3	0.6%	0.2%	-0.1%	-0.7%	-3.1%	3.8%	15.2
	4	0.6%	0.4%	-0.3%	-0.9%	-4.4%	5.0%	16.8
	5-high	0.2%	0.1%	-0.6%	-1.7%	-6.7%	6.9%	16.1
	1-5	0.2%	0.0%	0.5%	1.3%	4.9%		
	t-stat.	0.8	0.0	2.7	4.7	10.5		
IdioVOL-1F		1-low	2	3	4	5-high	1-5	t-stat.
	1-low	0.4%	0.1%	-0.1%	-0.4%	-1.6%	2.0%	13.5
	2	0.6%	0.2%	-0.1%	-0.4%	-2.3%	2.9%	14.4
	3	0.6%	0.2%	-0.1%	-0.7%	-3.1%	3.7%	15.8
	4	0.7%	0.2%	-0.2%	-1.0%	-4.5%	5.2%	16.4
	5-high	0.1%	0.0%	-0.9%	-1.9%	-6.9%	7.0%	15.9
	1-5	0.3%	0.1%	0.8%	1.5%	5.3%		
	t-stat.	1.5	0.7	4.6	5.6	11.1		
IdioVOL-3F		1-low	2	3	4	5-high	1-5	t-stat.
	1-low	0.5%	0.1%	0.0%	-0.4%	-1.6%	2.1%	13.7
	2	0.6%	0.2%	-0.1%	-0.5%	-2.2%	2.8%	14.0
	3	0.7%	0.3%	-0.1%	-0.6%	-2.9%	3.6%	16.2
	4	0.6%	0.3%	-0.3%	-1.0%	-4.5%	5.1%	16.7
	5-high	0.1%	0.0%	-0.9%	-2.0%	-6.9%	7.0%	15.6
	1-5	0.4%	0.1%	0.8%	1.6%	5.3%		
	t-stat.	1.8	0.6	5.0	5.9	11.1		

Panel B: Delta-hedged put returns

		Option Expensiveness (IV−HV)						
		1-low	2	3	4	5-high	1-5	t-stat.
VOL	1-low	0.1%	-0.1%	-0.3%	-0.6%	-1.8%	1.9%	15.4
	2	0.3%	-0.1%	-0.3%	-0.6%	-2.2%	2.5%	16.3
	3	0.3%	0.0%	-0.2%	-0.7%	-2.6%	3.0%	16.9
	4	0.3%	0.1%	-0.3%	-1.0%	-3.6%	4.0%	18.7
	5-high	-0.2%	-0.2%	-0.6%	-1.8%	-5.3%	5.0%	19.3
	1-5	0.3%	0.1%	0.4%	1.2%	3.4%		
	t-stat.	1.8	0.9	1.8	7.0	11.4		
		1-low	2	3	4	5-high	1-5	t-stat.
IdioVOL-1F	1-low	0.1%	-0.1%	-0.2%	-0.5%	-1.6%	1.8%	13.6
	2	0.3%	0.0%	-0.2%	-0.6%	-2.1%	2.4%	16.0
	3	0.4%	0.0%	-0.2%	-0.7%	-2.6%	2.9%	17.5
	4	0.4%	0.1%	-0.4%	-1.0%	-3.6%	4.0%	18.6
	5-high	-0.3%	-0.3%	-0.8%	-2.0%	-5.4%	5.1%	19.7
	1-5	0.5%	0.2%	0.6%	1.4%	3.8%		
	t-stat.	2.8	1.8	3.2	8.5	12.8		
		1-low	2	3	4	5-high	1-5	t-stat.
IdioVOL-3F	1-low	0.2%	0.0%	-0.2%	-0.5%	-1.7%	1.8%	14.0
	2	0.3%	0.0%	-0.2%	-0.6%	-2.0%	2.3%	15.2
	3	0.4%	0.1%	-0.3%	-0.6%	-2.6%	3.0%	17.2
	4	0.3%	0.0%	-0.3%	-1.0%	-3.6%	3.9%	19.1
	5-high	-0.4%	-0.3%	-0.8%	-2.0%	-5.5%	5.1%	19.9
	1-5	0.6%	0.3%	0.6%	1.5%	3.8%		
	t-stat.	3.3	2.1	3.5	8.7	13.1		

Note: This table shows average delta-hedged option returns of portfolios obtained via double sorts by stock return 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 June 2021, delta-hedged option returns are sorted by volatility (either VOL, IdioVOL-1F or IdioVOL-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 row denoted by 1-5 presents the results for a long–short trading strategy that buys the portfolios with the lowest volatilities (1-low) and sells the portfolios with the highest volatilities (5-high). The column denoted by 1-5 presents the results for a long–short trading strategy that buys the portfolios with the lowest expensiveness (1-low) and sells the portfolios with the highest expensiveness (5-high). The t-statistics for the average returns are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation of the portfolio returns.

The next analysis contrasts the unconditional effects from Table 2.2 with conditional effects. 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, IdioVOL-1F, or IdioVOL-3F in this sort. Next, we sort the returns in each volatility quintile by IV−HV and again build quintiles. For each of the 25 resulting groups, we calculate average returns. Finally, we obtain time-series averages of the mean returns in each group. Table 2.3 provides the results of these calculations. 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. The sixth column (1-5) delivers the results of long–short trading strategies that buy cheap options (low expensiveness, 1-low) and sell expensive options (high expensiveness, 5-high). Each expensiveness strategy in the sixth column uses a different volatility quintile. If there is an expensiveness effect, the returns of these strategies should be positive. The last column provides t-statistics for the returns. The first five rows (1-low to 5-high) refer to the respective volatility quintiles. The sixth row (1-5) contains the average returns of long–short trading strategies that buy the low-volatility portfolio (1-low) and sell the high-volatility portfolio (5-high). These low-volatility strategies are conditional on different expensiveness quintiles. If there is a low-volatility effect, the average return of these trading strategies should be positive. Finally, the last row reports t-statistics for the average returns of the 1-5 portfolios.

According to Hypothesis 1, the low-volatility effect should be stronger for options with high expensiveness than for options with low expensiveness. The results in Table 2.3 provide clear support for this hypothesis. 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 49-day returns of the 1-5 strategy, the effect is about four times bigger in the highest expensiveness quintile (4.9%) than in the second highest expensiveness quintile (1.3%) for call options. For put options, it is almost three times bigger (3.4% versus 1.3%). No significant low-volatility effect at all can be found in the two lowest expensiveness quintiles, meaning that the effect is only detectable in a fraction of the whole data set. The findings are in line with a rationale that high expensiveness provides useful conditioning information to infer the sign of the net position of market makers in specific option series. With respect to potential benefits for investors, 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 1-5 strategy are more than three times larger for calls (4.9% versus 1.4%) and for puts (3.4% versus 1.1%), as compared to a strategy based on all options. The reason is that no significant low-volatility effect exists if expensiveness is low. When using idiosyncratic volatility (IdioVOL-1F or IdioVOL-3F) instead of VOL for sorting, the conditional low-volatility effect for high expensiveness appears even stronger. This finding is in line with the dominant role of non-market volatility and non-hedgeable volatility for the price setting of market makers.

The returns of the different expensiveness strategies in the 1-5 column provide evidence on the conditional expensiveness effect. According to Hypothesis 2, the expensiveness effect should be stronger for options written on high-volatility stocks than for options written on low-volatility stocks. The table shows a monotonously increasing expensiveness effect for both calls and puts, which supports Hypothesis 2. The expensiveness effect is biggest in the highest volatility quintile, however, there is still a significant effect in the lowest volatility quintile. These findings are in line with a rationale based on the price setting of market makers. Market makers should charge a different premium depending on being net long or short in an option series even if the volatility of the corresponding stock is low. However, the difference in premiums should be bigger for options written on high-volatility stocks. In terms of its magnitude, the expensiveness effect is about three times bigger for high-volatility stocks than for low-volatility stocks (6.9% versus 2.2%) for calls. The return difference is also highly statically significant. For puts, the expensiveness effect is about two and a half times bigger for options written on high-volatility stocks (5.0% versus 1.9%). If one moves from VOL to IdioVOL-1F or IdioVOL-3F, differences are even slightly bigger, as expected. Compared to the unconditional strategy, the conditional expensiveness strategy for options written on high volatility stocks earns an additional 49-day average return of 2.7% (from 4.2% to 6.9%) for calls. For puts, the return difference between conditional and unconditional strategy is 1.7% (from 3.3% to 5.0%).

2.5 Benefits for Investors

In this section, we further explore the value of the conditional low-volatility and expensiveness effects for investors. Our first question is whether the returns of conditional trading strategies relate to some common factors that are priced either in stock or options markets. If the returns of such strategies 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.

We examine 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 2.3) and volatility according to the one-factor market model (IdioVOL-1F in Table 2.3). 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 when sorting all stocks according to IdioVOL-1F, 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 & Poor’s (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 volatility-related trading strategies. As shown by Driessen et al. (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.

Table 2.4: Regressions of Average Returns of Long–Short (1-5) Volatility Portfolios When Expensiveness is High (5-high) on Different Factors.

Panel A: Calls

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Alpha	5.39%*** (4.71)	5.25%*** (10.87)	5.25%*** (11.46)	5.30%*** (11.07)	4.96%*** (4.48)
MKT	0.121 (1.84)				−0.006 (−0.08)
SMB	0.014 (0.13)				−0.038 (−0.37)
HML	−0.018 (−0.19)				0.025 (0.26)
MOM	−0.020 (−0.34)				−0.011 (−0.21)
LowVol	−0.047 (−0.74)				−0.090 (−1.49)
ZB-STR Index		−0.008** (−2.19)		0.003 (0.65)	0.009* (1.65)
dVIX			−0.002*** (−4.12)		−0.001 (−1.17)
ZB-STR Stocks				−0.033*** (−2.73)	−0.034** (−2.22)
R^2_{adj}	0.049	0.012	0.064	0.035	0.085

Table 2.4 presents the results of time-series regressions that regress the delta-hedged option returns of the 1-5 volatility 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 of volatility risk, according to Model 3, and the variance risk premium, according to Model 2. However, these effects are not observable for puts and disappear in the full model (Model 5). The only factor that stays significant in the full model for both calls and puts is the average return of zero-beta straddles of individual stocks, indicating some correlation risk premium. Most importantly, for all models in Table 2.4, alphas are highly significant both statistically and economically. Therefore, we can conclude that the cross-sectional phenomenon of a conditional low-volatility effect in option markets is not just a compensation for standard common factor risks.

Panel B: Puts

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Alpha	2.67%***	3.79%***	3.79%***	3.81%***	2.57%***
	(3.38)	(12.45)	(12.59)	(12.70)	(3.32)
MKT	0.032				0.032
	(0.71)				(0.64)
SMB	−0.104				−0.115
	(−1.36)				(−1.54)
HML	−0.073				−0.061
	(−1.02)				(−0.81)
MOM	−0.001				−0.007
	(−0.03)				(−0.20)
LowVol	−0.034				−0.044
	(−0.84)				(−1.11)
ZB-STR Index		−0.001		0.004	0.005
		(−0.59)		(1.40)	(1.48)
dVIX			−0.0003		0.0002
			(−0.76)		(0.34)
ZB-STR Stocks				−0.017**	−0.018**
				(−2.06)	(−2.02)
R^2_{adj}	0.024	−0.002	0.001	0.011	0.033

Significance levels: *p<0.1; **p<0.05; ***p<0.01

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 2.3) and use IdioVOL-1F. Based on Fama's 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 2.5 provides the results of an analogous analysis for a conditional expensiveness strategy. This strategy holds a long position in options with low expensiveness (1-low) and a short positions in options with high expensiveness (5-high), using the highest volatility quintile (5-high in Table 2.3) and volatility according to the one-factor market model (IdioVOL-1F in Table 2.3). As Table 2.5 shows, similar conclusions can be drawn for the conditional expensiveness effect than for the conditional low-volatility effect. The explanatory power of the risk factors is low and only the market factor and the dVIX have

Table 2.5: Regressions of Average Returns of Long–Short (1-5) Expensiveness Portfolios When Volatility is High (5-high) on Different Factors.

Panel A: Calls

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Alpha	8.12%*** (5.85)	6.91%*** (15.74)	6.89%*** (16.23)	6.94%*** (15.69)	7.75%*** (6.06)
MKT	0.033 (0.62)				−0.137** (−1.99)
SMB	0.105 (0.85)				0.057 (0.50)
HML	−0.112 (−1.05)				−0.074 (−0.78)
MOM	−0.096* (−1.77)				−0.072 (−1.54)
LowVol	0.004 (0.07)				−0.035 (−0.57)
ZB-STR Index		−0.005 (−1.58)		0.002 (0.45)	0.007 (1.28)
dVIX			−0.001*** (−3.71)		−0.002** (−2.22)
ZB-STR Stocks				−0.020 (−1.64)	−0.016 (−1.01)
R^2_{adj}	0.022	0.002	0.044	0.008	0.055

a significant factor loading in the full model (Model 5) for calls. All alphas are still highly significant both statistically and economically.

The second question that we ask in this section is whether the conditional low-volatility and expensiveness effects are only present in specific periods. They may have existed in the early years of our data period but disappeared over time. If this were the case, the effects are likely to be a result of market inefficiencies that 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. Another event-related explanation is that low-volatility and expensiveness effects are a compensation for catastrophe risk. As the trading strategies use options, they may be very sensitive to extreme events. If performance were very bad in crisis periods, positive mean returns in normal times may just reflect a compensation for catastrophe risk. Our data set is well suited to provide evidence on such an explanation because it

Panel B: Puts

	Model 1	Model 2	Model 3	Model 4	Model 5
Alpha	4.72%***	5.09%***	5.08%***	5.10%***	4.60%***
	(6.53)	(19.38)	(19.61)	(19.25)	(6.69)
MKT	−0.014				−0.079*
	(−0.35)				(−1.75)
SMB	−0.041				−0.057
	(−0.62)				(−0.89)
HML	−0.114*				−0.102*
	(−1.74)				(−1.68)
MOM	−0.059**				−0.049*
	(−2.16)				(−1.77)
LowVol	−0.014				−0.026
	(−0.39)				(−0.78)
ZB-STR Index		−0.001		0.0002	0.002
		(−0.39)		(0.05)	(0.55)
dVIX			−0.0004		−0.001
			(−1.43)		(−1.41)
ZB-STR Stocks				−0.003	−0.002
				(−0.40)	(−0.20)
R^2_{adj}	0.026	−0.003	0.007	−0.006	0.031
Significance levels:				*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows the results of different regression models that regress the returns of a low-expensiveness trading strategy on different combinations of factors. Panel A provides the results for calls and Panel B the results for puts. The low-expensiveness trading strategy holds long positions in a low-expensiveness portfolio (1-low) and short positions in a high-expensiveness portfolio (5-high). These portfolios refer to the highest volatitliy quintiles (see Table 2.3) using IdioVOL-1F. Based on Fama's 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.

contains two crisis periods, the GFC and the COVID-19 pandemic. Following Aït-Sahalia et al. (2012), we use June 2007 as the first month of the GFC and consider December 2009 as the end of this crisis period. The COVID-19 crises covers the period from January 2020[17] until the end our data period in June 2021.

[17] For example, John and Li (2021) use January 2020 as the starting month for their analysis of price dynamics in stock and option markets during the COVID-19 pandemic.

Table 2.6: Average Returns and Alphas of Long–Short (1-5) Volatility Portfolios When Expensiveness is High (5-high) for Different Periods.

Panel A: Calls

	Full Period	excl. Crises	Crises only	<04/2003	⩾04/2003
Average Return	5.32%***	4.71%***	8.61%***	3.14%***	6.20%***
	(11.15)	(16.95)	(4.22)	(10.30)	(10.47)
Alpha	4.96%***	6.97%***	2.73%	3.63%***	4.20%*
(Eight-Factor Model)	(4.48)	(6.97)	(0.75)	(3.20)	(1.82)

Panel B: Puts

	Full Period	excl. Crises	Crises only	<04/2003	⩾04/2003
Average Return	3.80%***	3.47%***	5.58%***	1.76%***	4.62%***
	(12.76)	(14.17)	(5.35)	(5.68)	(14.84)
Alpha	2.57%***	3.39%***	−0.66%	2.14%***	1.12%
(Eight-Factor Model)	(3.32)	(5.02)	(−0.29)	(3.30)	(0.87)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

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 2.3) and use IdioVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 2.4. The full data period is from January 1996 to June 2021. The crisis period of the GFC is from June 2007 to December 2009 and the crisis period of COVID-19 is from January 2020 to June 2021. The t-statistics (in parentheses) are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation.

Tables 2.6 and 2.7 provide the average returns and alphas (according to Model 5 in Tables 2.4 and 2.5) for five different time periods. We consider the full period (January 1996 to June 2021), the period until the SEC's market linkage plan became effective (January 1996 to March 2003), the period thereafter (April 2003 to June 2021), the full period excluding the times of the GFC (June 2007 to December 2009) and the COVID-19 pandemic (January 2020 to June 2021), and the crises periods only.

According to Table 2.6, there is no evidence that the conditional low-volatility effect disappeared during the later years of our data period. To the contrary, if we use the more recent period from April 2003 onwards, mean returns are higher than for the early years of the 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. Table 2.7 delivers the corresponding results for the conditional expensiveness effect. For both calls and puts, average returns are very similar before and after the SEC's market

Table 2.7: Average Returns and Alphas of Long–Short (1-5) Expensiveness Portfolios When Volatility is High (5-high) for Different Periods.

Panel A: Calls

	Full Period	excl. Crises	Crises only	<04/2003	⩾04/2003
Average Return	6.95%***	6.44%***	9.67%***	6.91%***	6.96%***
	(15.91)	(22.60)	(5.31)	(14.53)	(12.36)
Alpha	7.75%***	8.07%***	8.21%**	7.85%***	7.28%***
(Eight-Factor Model)	(6.06)	(6.40)	(2.23)	(4.06)	(3.65)

Panel B: Puts

	Full Period	excl. Crises	Crises only	<04/2003	⩾04/2003
Average Return	5.10%***	4.83%***	6.52%***	5.20%***	5.06%***
	(19.69)	(24.00)	(6.61)	(17.18)	(15.18)
Alpha	4.60%***	5.06%***	3.78%*	5.27%***	3.84%***
(Eight-Factor Model)	(6.69)	(7.35)	(1.76)	(5.09)	(3.70)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns and alphas of a low-expensivenss trading strategy for different time periods. Panel A provides the results for calls and Panel B the results for puts. The low-expensiveness trading strategy holds a long position in a low-expensiveness portfolio (1-low) and a short position in a high-expensiveness portfolio (5-high). These portfolios refer to the highest volatility quintiles (see Table 2.3) and use IdioVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 2.5. The full data period is from January 1996 to June 2021. The crisis period of the GFC is from June 2007 to December 2009 and the crisis period of COVID-19 started is from January 2020 to June 2021. The t-statistics (in parentheses) are obtained via Newey–West estimators (Newey and West, 1987), which account for heteroskedasticity and autocorrelation.

linkage plan became effective. Therefore, there is no indication that the large positive returns of the expensiveness trading strategies just stem from the early years of the data period. With respect to alpha, results are mixed. The alpha of the conditional volatility strategy increases after March 2003 for calls but decreases for puts. For the conditional expensiveness strategy, alpha somehow decreases from the early to the later data period for both calls and puts. The effects are, however, still large and statistically significant. The results on alpha could be due to the learning of the market with respect to the pricing of common risk factors. They could also be due to the difficulties to specify an appropriate factor model for options and the instability of alpha estimates when risk premiums are time-varying.

The returns in crisis periods provide no evidence that positive returns in normal periods are eaten up by large losses in crisis periods, indicating a compensation for catastrophe risk. To the contrary, average returns are always higher in crisis periods than in normal periods. This is true for calls and put as well as low-volatility strategies and expensiveness strategies. The finding is important for investors, as assets with positive returns in periods of crisis are particularly valuable. Results on alpha are again mixed. However, due to the relatively small number of observation and the large market movements during crisis periods, the estimation of factor models is likely to be unreliable.

The third question of this section is whether the conditional low-volatility and expensiveness effects can be exploited by investors via simple trading strategies even in the presence of transaction costs. So far, our analysis of the low-volatility and expensiveness trading strategies 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).[18] The effective spread is defined as twice the difference between the execution price and the mid price at the beginning of the option return period. Specifically, we assume ESPR/QSPR ratios of 10%, 25%, and 50%, as in Cao and Han (2013), plus a ratio of 75%. As a reference point, we also repeat results under the assumption of no transaction costs (i.e., mid price [MidP]).

Table 2.8 reports the average delta-hedged option returns and alphas (according to Model 5 in Table 2.4) of the 1-5 volatility strategy 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% in most cases (the exception is the eight-factor alpha for puts). If we move to 50%, however, we lose significance in most cases (the exception is the average return for puts). With a ESPR/QSPR ratio of 75%, all average returns and alphas are negative. In conclusion, only investors with low transactions costs can exploit the conditional low-volatility effect profitably, though the effect is three times stronger than the unconditional low-volatility effect. For the conditional expensiveness effect, which is generally stronger than the conditional low-volatility effect, we reach the same conclusion. According to the results in Table 2.9, transaction costs equal to 75% of the quoted spread decrease returns and alphas completely or at least make them

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

Table 2.8: Effect of Transaction Costs on Average Returns and Alphas of Long–Short (1-5) Volatility Portfolios When Expensiveness is High (5-high).

Panel A: Calls

ESRP/QSPR	MidP	10%	25%	50%	75%
Average Return	5.32%***	4.28%***	2.80%***	0.43%	−1.85%***
	(11.15)	(10.44)	(8.33)	(1.44)	(−4.96)
Alpha	4.96%***	4.08%***	2.82%***	0.78%	−1.15%
(Eight-Factor-Model)	(4.48)	(3.95)	(2.89)	(0.79)	(−1.02)

Panel B: Puts

ESRP/QSPR	MidP	10%	25%	50%	75%
Average Return	3.80%***	3.14%***	2.14%***	0.41%**	−1.40%***
	(12.76)	(11.82)	(9.63)	(2.18)	(−5.80)
Alpha	2.57%***	1.98%***	1.10%*	−0.40%	−1.95%***
(Eight-Factor-Model)	(3.32)	(2.74)	(1.67)	(−0.66)	(−2.97)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

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 2.3) and use IdioVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 2.4. The data period is from January 1996 to Jun 2021. The different transaction cost scenarios refer to different ratios of ESPR to QSPR: 10%, 25%, 50%, or 75%. 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.

statistically insignificant. Only investors with low transaction costs will be able to exploit the conditional expensiveness effect profitably via a long-short strategy.

These findings, however, do not mean that knowledge of the conditional low-volatility or expensiveness effects is useless for investors with higher transactions costs. To the contrary, our findings show that the effects cannot be easily arbitraged away (due to the transactions costs) and do neither shrink over time nor deteriorate in periods of crisis. It is thus plausible and backed by intermediary asset pricing theory that the effects will persist in the future. They should therefore be considered by investors. 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 expensiveness effect in the highest quintile. If we take the results from Table 2.3, the differences in average

Table 2.9: Effect of Transaction Costs on Average Returns and Alphas of Long–Short (1-5) Expensiveness Portfolios When Volatility is High (5-high).

Panel A: Calls

ESRP/QSPR	MidP	10%	25%	50%	75%
Average Return	6.95%***	5.77%***	4.08%***	1.38%***	−1.23%***
	(15.91)	(15.12)	(12.15)	(3.77)	(−2.58)
Alpha	7.75%***	6.73%***	5.25%***	2.84%*	0.47%
(Eight-Factor-Model)	(6.06)	(5.16)	(3.79)	(1.80)	(0.26)

Panel B: Puts

ESRP/QSPR	MidP	10%	25%	50%	75%
Average Return	5.10%***	4.33%***	3.19%***	1.23%***	−0.80%**
	(19.69)	(18.28)	(14.51)	(4.95)	(−2.33)
Alpha	4.60%***	3.92%***	2.91%***	1.19%	−0.56%
(Eight-Factor-Model)	(6.69)	(5.49)	(3.73)	(1.27)	(−0.49)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns and alphas of a low-expensivenss trading strategy for different levels of transaction costs. Panel A provides the results for calls and Panel B the results for puts. The expensiveness trading strategy holds long positions in a low-expensiveness portfolio (1-low) and short positions in a high-expensiveness portfolio (5-high). These portfolios refer to the highest volatility quintiles (see Table 2.2) and use IdioVOL-1F. Alphas are obtained from the eight-factor model (Model 5) in Table 2.5. The data period is from January 1996 to June 2021. The different transaction cost scenarios refer to different ratios of ESPR to QSPR: 10%, 25%, 50% or 75%. 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.

49-day delta-hedged returns (using IdioVOL-1F) when selecting options on high-volatility stocks from the lowest IV−HV quintile instead of the highest quintile would be 7% for calls and 5.1% for puts.[19]

2.6 Conclusions

The low-volatility and expensiveness effects are well-known phenomena in options markets. This paper re-examines these effect from the unifying perspective of intermediary asset pricing theory. It suggests a linkage between the two effects that results in hypotheses on their conditional properties, where one effect is investigated conditional on the magnitude of the other. In particular, it is hypothesized that the low-volatility effect is primarily

[19]The calculations in Table 2.3 are based on option mid quotes and daily adjustments of the delta-hedges. If we take transaction costs into account by using ask prices of options and leaving the initial stock position unchanged, the differences in 49-day initially delta-hedged returns are even higher.

present for expensive options and that the expensiveness effect increases with volatility. Both hypotheses are confirmed in an empirical study.

Our empirical findings support the view that market imperfections and the reaction of market makers to these imperfections are important for the understanding of options markets. If high option expensiveness is a good proxy for market makers being net short in options and high idiosyncratic volatility is a good proxy for severe market imperfections, the observed patterns 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. The difference in compensation for long and short positions should grow with market imperfections, which is in line with the conditional expensiveness effect. More generally, our analysis complements demand-based explanations of the low-volatility and expansiveness effects by drawing attention to the potential costs to meet a certain demand.

The effects that we document in this paper also provide important information for investors in options markets. First, the conditional effects are much stronger than the unconditional ones. Second, they cannot be explained by common factor risks in stock and option markets and therefore offers some potential to create alpha. Finally, they are stable over time and cannot easily be arbitraged away in the presence of transaction costs. Therefore, the effects are likely to persist in the future and should be considered in the design of investment strategies in stock options.

Of course, the low-volatility and expensiveness effects are just two patterns that exist in the cross-section of option returns. Current empirical research has discovered a variety of other regularities. For example, Bali et al. (2022) and Shafaati et al. (2022) use advanced econometric methods to identify unknown structures, Horenstein et al. (2022) and Zhan et al. (2022) show that firm characteristics like size and profitability are priced in options markets, and Yang et al. (2022) find significant premiums for consumption growth and consumption volatility in the cross-section of delta-hedged option returns. In the end, all the observed patterns require a convincing economic explanation. What our paper has shown is that different effects may be linked via a common economic rationale. This route may also be fruitful for a better understanding of other regularities in the cross-section of option returns.

3 Exposures of Delta-Hedged Option Portfolios

Abstract

I analyze the exposures of delta-hedged option portfolios using a large data set of options on 7,320 different stocks. I find that options have exposure to volatility, skewness as well as kurtosis of their underlying's return distribution of which especially the idiosyncratic parts are important. Further, options have exposure to volatility and skewness uncertainty as well as to certain firm characteristics which are shown to be priced in delta-hedged option returns. Firm characteristics are especially informative when the moments indicate low risk of the underlying. They may serve as alternative risk measures in times when historical stock return moments indicate low risk.

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3.1 Introduction

Option returns are of great interest in financial research with studies focusing on the determinants of index option returns (e.g., Bakshi and Kapadia, 2003a; Broadie et al., 2009) as well as individual equity option returns (e.g., Cao and Han, 2013; Byun and Kim, 2016; Zhan et al., 2022). Most studies in the option literature study expected option returns and many option- and firm characteristics are shown to affect them. However, little is known about the exposures of options and the determinants of realized option returns although options are widely used for many different reasons. For example, individual investors use equity options mostly for speculation (Lakonishok et al., 2007; Bauer et al., 2009), hedge funds use equity options for volatility timing and to profit from their stock-picking skills (Aragon and Martin, 2012) and mutual funds use mostly equity options to hedge their systematic risk and improve their risk-adjusted returns (Natter et al., 2016). However, not only end-users who use options in their investment strategies need to know their exposures but also market makers who provide liquidity to the option markets (Giannetti et al., 2004; Cao and Han, 2013). Regardless of the designated use of options, every market participant needs to know their risk exposure and its economic magnitude to apply an appropriate risk management strategy. Additionally, the exposures are not only crucial knowledge to market participants but are also important for financial research. While firm characteristics are known to be priced in option returns, the pricing channels remain puzzling (Zhan et al., 2022). An exposure analysis sheds more light on potential reasons why these characteristics are priced.

To the best of my knowledge, this is the first paper to analyze the economic magnitude of option exposures using a large cross-section of delta-hedged option returns. This allows me to give new insights into the behaviour of delta-hedged option portfolios with respect to changes of different kinds of risks as well as firm characteristics. While the effect of innovations in the stock return volatility (and probably kurtosis) of a firm on delta-hedged option returns might be conceivable, the effect of skewness on delta-hedged option returns is not so clear. Generally, the payoff profile of a delta-hedged option portfolio depends on the moneyness of the option. It changes between the payoff profile of a call and that of a put. The following explanations illustrate the case of a delta-hedged call option portfolio.

For a put option portfolio, all payoff profiles are mirrored.[20] There are three important moneyness levels that illustrate the range of payoff profiles of delta-hedged option portfolios: (deep) out-of-the-money (OTM), at-the-money (ATM) and (deep) in-the-money (ITM). Although the options in this study are required to be closest to ATM at the beginning of the option return period, the other two cases (i.e., ITM and OTM) are relevant as well for two reasons: i) the selected options are rarely exactly ATM[21], and ii) even when the options are ATM at the beginning of the option return period, their moneyness is likely to change because of stock price movements during the option return period which pushes the option into the money or out of the money. The first illustration shows the case when the option is at-the-money. The delta of an ATM option equals 0.5.[22] In the case of a delta-hedged call option portfolio, the portfolio consists of a call and short position of half a stock for every stock the option is written on. Together, the payoff profile of the delta-hedged option portfolio is symmetric and equals that of half a straddle. Figure 3.1 illustrates this case.

Second, if a call option is deep out-of-the-money, the delta is close to zero which results in a portfolio which consists entirely of the call. Hence, the payoff profile of the total position equals that of the call. Figure 3.2 illustrates this case.

Lastly, if the call is deep in-the-money, the delta is close to one which results in a portfolio with one call and one short position for every stock the option is written on.[23] Hence, the payoff profile of the total portfolio equals that of a put option. Figure 3.3 illustrates this case.

Even knowing these stylized payoff profiles, the effect of changes of the higher moments is not easy to see, especially in the case of skewness. The skewness of a stock decreases the probability mass of the left tail of the return distribution. This increases the likelihood of

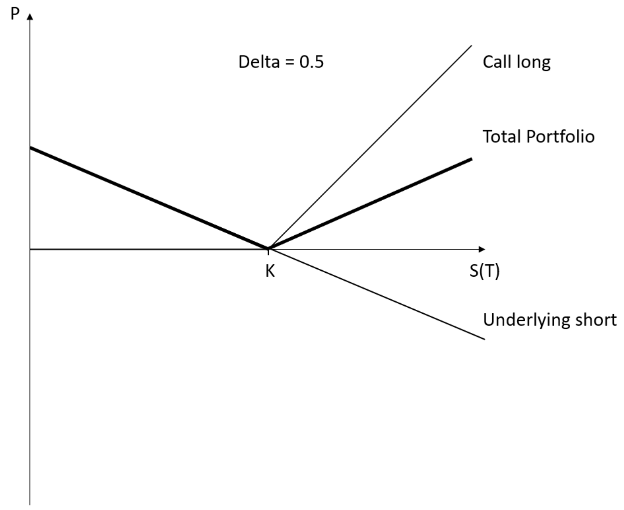
[20]In case of a delta-hedged put option portfolio, the position in the underlying becomes a long position. If the put option has the same strike price as the call option, both delta-hedged option portfolios have the same overall payoff profile at a given stock price level, since the put is out-of-the-money when the call with the same strike price is in-the-money and vice versa.

[21]The moneyness range that options must fall into is [0.8;1.2]. The option selection process will be further explained in Section 3.2.2.

[22]Note that the illustrations in Figures 1-3 show stylized payoff profiles which are supposed to show the functional form and the symmetry of the payoff profiles of a delta-hedged call option portfolio rather than the actual levels of the payoffs. Hence, the x-axis does not necessarily coincide with zero.

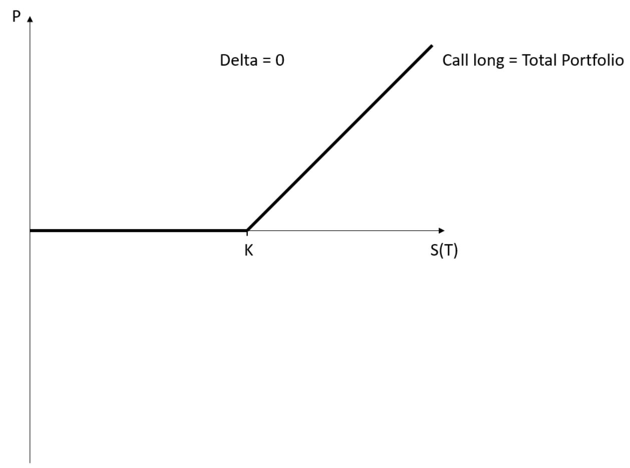
[23]Options are typically written on 100 stocks which results in a short position of 100 stocks in the case of the option being deep in-the-money.

Figure 3.1: Stylized Payoff Profile of a Delta-Hedged Call Option Portfolio when the Option is At-The-Money



Note: This figure shows the stylized payoff profile of a delta-hedged option portfolio that is set up with an ATM-option with a delta of 0.5. Hence, it shows the stylized payoff profile of a portfolio that consists of a call option with strike price K and an underlying-position.

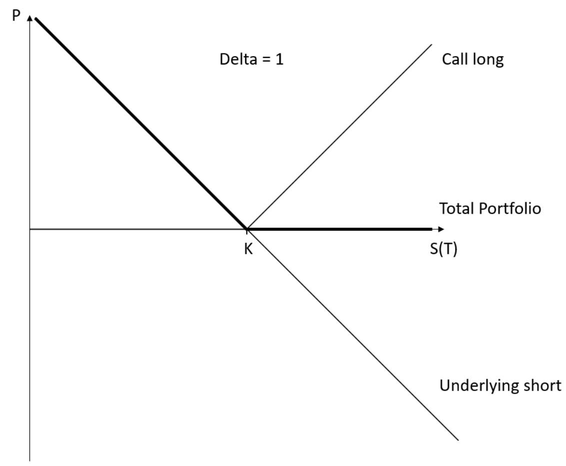
Figure 3.2: Stylized Payoff Profile of a Delta-Hedged Call Option Portfolio when the Option is Out-Of-The-Money



Note: This figure shows the stylized payoff profile of a delta-hedged option portfolio that is set up with an OTM-option with a delta of 0. Hence, it shows the payoff profile of call option with strike price K which equals the resulting stylized payoff profile of the total portfolio because their is no position in the underlying.

the stylized payoff profile of the portfolio being changed to that of a call. However, it is not clear whether this increases the average return of the delta-hedged option portfolio since the linear effect of the underlying (i.e., the negative returns) are hedged away. Moreover, this ambiguity increases when it comes to exposure to the idiosyncratic and systematic

Figure 3.3: Stylized Payoff Profile of a Delta-Hedged Call Option Portfolio when the Option is In-The-Money



Note: This figure shows the stylized payoff profile of a delta-hedged option portfolio that is set up with an ITM-option with a delta of 1. Hence, it shows the stylized payoff profile of a portfolio that consists of a call option with strike price K and an underlying-position.

parts of the moments and it is not clear whether both are important (and to what extent). Therefore, it is fruitful to study the behaviour of delta-hedged option portfolios especially to innovations in the third moment of their underlying's return distributions. But not only the moments of the underlying's return distribution are known to affect option returns but also firm characteristics which is shown by Zhan et al. (2022). Building on these results, I analyze the effect of firm characteristics on realized delta-hedged option returns. Because firm characteristics are known to affect the riskiness of a firm (e.g., Cheng, 2008), they can be interpreted as alternative risk measures. To analyze whether firm characteristics provide additional information, I study the interaction with the moments of the firms' return distributions (as more direct measures of a firm's risk). Hence, I analyze the triangular relation between the firm characteristics, delta-hedged option returns and the moments of the options' underlying's return distributions.

For my analyses, I use a rich data set of individual equity options on 7,320 different stocks over the period from January 1996 to June 2021. I use delta-hedged option returns following the calculation of Bakshi and Kapadia (2003a,b). Further, I use moments of the underlying stocks' return distributions as well as the moment risks which I obtain from daily stock returns. For the decomposition into the idiosyncratic and systematic part of the risk measures, I use specific factor portfolios from Kenneth French's data library.

Additionally, I use firm characteristics that have been shown to be priced in delta-hedged option returns (Zhan et al., 2022).

My analyses provide the following main results: i) delta-hedged option portfolios have exposure to the second, third and fourth moment of their underlying's return distribution in the direction that is consistent with investor preferences (Dittmar, 2002), ii) mainly the idiosyncratic parts of the moments drive the exposure, iii) delta-hedged option portfolios also have exposure to the moment risks of the second and third moment (but not to the moment risk of the fourth moment), iv) as for the moment risks, the idiosyncratic and systematic parts both matter with different signs while the idiosyncratic parts are more highly significant than their systematic counterpart, v) delta-hedged option portfolios have exposure to most (but not all) firm characteristics studied by Zhan et al. (2022) (there seems to be no general exposure to changes in the cash flow variance and the total external financing), vi) The relationship between delta-hedged option portfolios and firm characteristics is especially informative when the stock return moments indicate low risk suggesting that firm characteristics act as alternative risk measures.

This paper contributes to the strand of literature studying delta-hedged option portfolios in the cross-section. The vast majority of these papers studies the determinants of expected delta-hedged option returns. Different risk measures and firm characteristics have been discovered to be priced in expected delta-hedged option returns. One of the first studies is that of Bakshi and Kapadia (2003b) who show that delta-hedged option returns significantly underperform the risk-free rate. They argue that this finding is driven by a negative variance risk premium in a stochastic volatility model. Goyal and Saretto (2009) show that delta-hedged option returns increase with the difference between the historical and implied volatility and explain this behaviour with volatility mispricing. While Bakshi and Kapadia (2003b) argue that idiosyncratic volatility is not priced and delta-hedged option returns are driven by a systematic risk factor, Cao and Han (2013) show that the idiosyncratic volatility is priced in expected delta-hedged option returns as well which they explain with the pricing behaviour of market makers because of inventory risk resulting from unhedgeable risks. But also the higher moments are shown to be priced in expected option returns. Byun and Kim (2016) as well as Bali et al. (2022) show that the skewness and kurtosis are priced in delta-hedged option returns which they explain with a lottery preference of investors. Further, since volatility is stochastic and therefore risky itself, it is sensible to study whether this volatility uncertainty is priced as well. Cao et al. (2019) as well as Ruan (2020) show that volatility uncertainty measured as the vol-of-vol affects expected delta-hedged option returns as well. Additionally, Bollen and Whaley (2004), Gârleanu et al. (2009), Muravyev (2016) as well as Ramachandran and Tayal (2021) show that demand pressure is also driving expected delta-hedged option returns. Even the characteristics of the underlyings are priced in delta-hedged option returns. Zhan et al. (2022) show that firm characteristics prominent from known pricing anomalies of the stock market affect expected delta-hedged option returns. The pricing of these characteristics is even present when they control for the aforementioned risk measures.[24] Apart from the pricing of certain risk measures and firm characteristics, also the factor structure of option prices and expected delta-hedged option returns has been studied. Christoffersen et al. (2018a) find that option prices show a strong factor structure. Horenstein et al. (2022) show that a four-factor model with the variables firm size, idiosyncratic volatility, the difference between the historical and the implied volatility as well as the delta-hedged option return of S&P 500 index options explains the cross-sectional variation of expected option returns. Additionally, Shafaati et al. (2022) use a LASSO estimator to determine the dominant characteristics to explain the cross-sectional variation of expected option returns. They find the innovation in the implied volatility, the idiosyncratic volatility, the firm size, accruals as well as the number of zero-trading days as to be these dominant factors.

My paper contributes to this strand of literature by analyzing the exposures of realized option returns and therefore shedding more light on the properties and determinants of delta-hedged option returns. More specifically, I show that especially the idiosyncratic parts of volatility, skewness and kurtosis are affecting realized delta-hedged option returns which emphasizes the importance of idiosyncratic risks. Additionally, I shed light on the exposure to the uncertainty of these moments as well as to firm characteristics. These analyses enhance the understanding of delta-hedged option portfolios and their exposures which are crucial knowledge for risk management. Further, the results also enable for a review of the pricing which was discovered in the above studies because it is questionable why a risk measure or firm characteristic is priced when delta-hedged option portfolios have

[24]Note that Zhan et al. (2022) study expected delta-hedged option returns. The discovered pricing of these firm characteristics can therefore not be explained by the stock returns of the underlyings.

no exposure to them. Although the studies by Christoffersen et al. (2018a), Horenstein et al. (2022) as well as Shafaati et al. (2022) study the factor structure of option prices and expected returns and are therefore closely related, their focus is different than mine. These studies try to explain the cross-sectional variation of option prices and expected returns. In my study, I focus on the question which risk measures and firm characteristics affect realized delta-hedged option returns. In other words, I shed light on the question which risks investors and market makers still have in their portfolios when delta-hedging their option positions.

The remainder of the paper is organized as follows. In Section 3.2, the data and the methodology of the empirical study is described. Further, the calculation of delta-hedged option returns as well as the calculation methodology of the stock return moments and moment risks will be introduced. Subsequently, Section 3.3 shows the empirical results of the exposure analysis of delta-hedged option portfolios to the stock return moments as well as the moment risks. Further, the exposures to firm characteristics are analyzed. Finally, the triangular relationship between firm characteristics, delta-hedged option returns and stock return moments are shown. Section 3.4 concludes the study.

3.2 Data and Methodology

3.2.1 Data Sources and Filters

For the analyses, I use different data sources for my options data and for firm-specific data. The main data source for my options and stock return data[25] is the OptionMetrics IvyDB database. This database contains daily information about options like best bids, best asks, trading volume, strike, time-to-maturity as well as the option Greeks of all US-listed index and equity options from January 1996 until June 2021. The Greeks as well as the implied volatilities are calculated by OptionMetrics and their proprietary algorithms. I use data from January 1996 to June 2021 and all individual options data is kept in the data sample. The resulting data sample is then filtered using common filters from previous studies (e.g., Bakshi and Kapadia, 2003b; Goyal and Saretto, 2009; Cao and Han, 2013). To avoid biases related to the market microstructure, I exclude all observations with a bid-price of zero or above the ask-price, the bid-ask spread is required to be above the

[25] Analogous to Chapter 2, I obtain the stock return data from the IvyDB database as well.

minimum tick size and the mid price must be higher than \$1/8. Additionally, I apply the common no-arbitrage filters: $\max\left(S - Ke^{-r\tau}; 0\right) \leqslant C \leqslant S$, where C represents the price of a call option, K is the strike price, r is the risk-free rate, S is the price of the underlying and τ is the time-to-maturity. Further, I exclude all options with a missing delta at the beginning of the option return period as well as options whose underlying stock pays a dividend during the option return period.[26] The accounting data for the calculation of the firm characteristics is obtained from CompuStat. Lastly, I use Kenneth French's data library to obtain daily returns of specific factor portfolios. The portfolio returns are used to distinguish between the idiosyncratic and the systematic part of the stock return moments and moment risks.

3.2.2 Delta-Hedged Option Returns

My calculation of delta-hedged option returns follows previous studies (e.g., Bakshi and Kapadia, 2003b; Cao and Han, 2013; Zhan et al., 2022). At the end of each month, I choose a put-call pair whose moneyness[27] is closest to at-the-money and must be in the range [0.8; 1.2] and with a time-to-maturity that is the shortest after one month.[28] The delta-hedged option return is then calculated from a dynamically rebalanced portfolio consisting of the option, the underlying and a risk-free bond. The call (put) is delta-hedged with the underlying stock and a risk-free bond over the period $[t;\, t+\tau]$. The portfolio is therefore discretely rebalanced on a daily basis at the dates t_n with $n = 0, \ldots, N-1$, where t_0 refers to the date at which the delta-hedged position is set up and t_{N-1} is the last trade day before option expiry. The resulting delta-hedged option return is then defined as:

$$R^C_{t,t+\tau} = \frac{C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta^C_{t_n} \left[S_{t_{n+1}} - S_{t_n}\right] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left[C_{t_n} - \Delta^C_{t_n} S_{t_n}\right]}{Abs(C_t - \Delta^C_t S_t)}, \tag{3.1}$$

[26] Options on individual stocks are American type, but because of the lack of dividend payments during the option return period, call options in my sample are effectively European options. For puts, the early exercise premium is only reduced because even without dividend payments, if the American put option is sufficiently deep ITM, it is optimal to exercise it early.

[27] I calculate the moneyness of an option as the ratio of spot price to strike for calls and strike to spot price for puts.

[28] Although the range [0.8;1.2] is commonly defined as ATM, it already leads to payoff profiles that deviate from that in figure 3.1. Depending on whether the moneyness of the option is below 1 (i.e., OTM) or above 1 (i.e., ITM), the payoff profile is between figure 3.1 and figure 3.2 (OTM) or between figure 3.1 and figure 3.3 (ITM).

$$R^P_{t,t+\tau} = \frac{P_{t+\tau} - P_t - \sum_{n=0}^{N-1} \Delta^P_{t_n} \left[S_{t_{n+1}} - S_{t_n}\right] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left[P_{t_n} - \Delta^P_{t_n} S_{t_n}\right]}{Abs(P_t - \Delta^P_t S_t)}, \tag{3.2}$$

where C and P represent the price of a call and put, respectively, at time t and with expiration in time $t + \tau$. S refers to the spot price of the underlying at time t, r is the risk-free rate, a_n is the number of calender days between t_n and t_{n+1} and Δ represents the option's delta (i.e., the number of stocks held for the delta-hedge). The Equations (3.1) and (3.2) represent the dollar gains of the delta-hedged portfolio scaled by the absolute value of the positions in the securities involved in the delta hedge to make the returns comparable across options on different stocks. The returns can therefore be interpreted as the excess returns over the risk-free rate.

After selecting and filtering the data, observations from $501,800$ call options and $500,371$ put options of $7,320$ firms remain in the final sample. Given the data period of 306 months, I have on average $1,640$ calls and $1,635$ puts per months. Important to note, however, is that the actual numbers of observations per month increase over time, i.e., I have less observations per month in 1996 and more observations per month in 2021. Descriptive statistics are shown in Table 3.1. Panel A provides an overview over the distribution of the call option characteristics, while Panel B shows the same for the put option observations in my sample.

The delta-hedged option returns for both calls and puts are negative on average with -0.9%, and show a large dispersion with a standard deviation of 9.4% and 7.8% for calls and puts, respectively. The quantiles show that the 10% and 90% quantiles of delta-hedged call (put) option returns range from -7.8% (-6.7%) to 5.7% (4.7%) and the interquartile range in which 50% of the observations are, is 5.3% (4.6%) with the lower quartile at -3.7% (-3.4%) and the upper quartile at 1.6% (1.2%). The time-to-maturity is 48.8 days on average with a standard deviation of 4.1 days for calls and puts, respectively. The 10% and 90% quantiles ranges from 46 to 52 days for both puts and calls. The moneyness has a mean of 1 and a standard deviation of 0.05 for both option types, ranging, by definition, from 0.8 to 1.2.

Table 3.1: Summary Statistics of Options and Stock Data

Panel A: Call Options (501,800 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.9%	9.4%	–7.8%	–3.7%	1.6%	5.7%
Days to Maturity	48.8	4.1	46.0	49.0	51.0	52.0
Moneyness (S/K)	1.00	0.05	0.93	0.97	1.03	1.06

Panel B: Put Options (500,371 observations)

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Delta-Hedged Return	–0.9%	7.8%	–6.7%	–3.4%	1.2%	4.7%
Days to Maturity	48.8	4.1	46.0	49.0	51.0	52.0
Moneyness (K/S)	1.00	0.05	0.94	0.97	1.03	1.06

Panel C: Stock Return Moments

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Volatility	0.47	0.28	0.20	0.27	0.58	0.82
IdioVol	0.40	0.25	0.16	0.23	0.51	0.72
SysVol	0.20	0.16	0.05	0.09	0.25	0.40
Skewness	0.15	1.05	-0.89	-0.31	0.61	1.25
IdioSkew	0.18	1.16	-1.01	-0.32	0.70	1.44
SysSkew	-0.13	0.56	-0.83	-0.44	0.21	0.52
Kurtosis	1.76	3.54	-0.58	-0.18	2.05	5.50
IdioKurt	2.16	3.89	-0.52	-0.09	2.60	6.77
SysKurt	0.45	1.23	-0.73	-0.36	0.85	2.09

Panel D: Stock Return Moment Risks

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Scaled Vol-of-Vol	0.38	0.17	0.22	0.27	0.45	0.59
Scaled Vol-of-IdioVol	0.39	0.18	0.23	0.28	0.46	0.60
Scaled Vol-of-SysVol	0.63	0.21	0.40	0.48	0.75	0.91
Vol-of-Skew	0.85	0.32	0.48	0.60	1.05	1.30
Vol-of-IdioSkew	0.89	0.32	0.51	0.65	1.10	1.34
Vol-of-SysSkew	0.57	0.18	0.31	0.44	0.63	0.88
Scaled Vol-of-Kurt	2.34	12.85	-2.69	1.53	3.39	6.45
Scaled Vol-of-IdioKurt	2.32	10.27	-0.87	1.55	3.16	5.47
Scaled Vol-of-SysKurt	0.23	6.09	-6.88	-2.96	3.91	5.02

3.2.3 Stock Return Moments

As a starting point of my analyses, I use the second, third and fourth moment of the return distributions of the options' underlyings (i.e., the volatility, the skewness and the kurtosis) as well as their moment risks (i.e. the volatility of the moments) to gain insights into the exposure of delta-hedged option returns against them. Additionally, I decompose the total moments into their idiosyncratic and their systematic part to gain further insights into

Panel E: Firm Characteristics

	μ	σ	$q_{0.1}$	$q_{0.25}$	$q_{0.75}$	$q_{0.9}$
Cashflow Variance	0.01	0.09	0.000003	0.00001	0.0004	0.003
Cash-to-Assets Ratio	0.20	0.23	0.01	0.03	0.28	0.55
Ln(Price)	3.14	1.02	1.79	2.55	3.83	4.32
Profitability	0.02	0.77	-0.32	-0.01	0.16	0.27
Profit Margin	-0.50	4.97	-0.15	0.03	0.20	0.35
Share Issuance 1Y	0.04	0.12	-0.04	-0.01	0.03	0.14
Total External Financing	0.01	0.08	-0.04	-0.005	0.02	0.09
Z-Score	5.12	7.68	0.73	1.81	5.78	10.90

Note: This table shows the summary statistics of the options, stock return moment, moment risk and firm characteristics data that is used in the empirical study. Shown are the mean (μ), the standard deviation (σ), the 10% quantile ($q_{0.1}$), the 25% quantile ($q_{0.25}$), the 75% quantile ($q_{0.75}$) as well as the 90% quantile ($q_{0.9}$) of the respective variable.The calculations include data from January 1996 to June 2021. In Panel A, the summary statistics of call options is shown. It shows the delta-hedged option return following the calculation as given in Equation (3.1), the time-to-maturity in (calendar) days as well as the moneyness defined as the ratio of stock price(S) and strike price (K). Analogously, Panel B shows the summary statistics of put options. The delta-hedged put option return is calculated as given in Equation (3.2). Panel C shows the summary statistics of the stock return moments including volatility, skewness and kurtosis and their idiosyncratic and systematic risk parts which I distinguish using a one-factor market model. The volatility measures are annualized and calculated from daily returns over the option return periods. Panel D shows the stock return moment risks. The calculation of the scaled vol-of-vol follows that given by Baltussen et al. (2018): for every month, we calculate the standard deviation of the daily stock returns; afterwards, we calcalculate the standard deviation of the twelve standard deviations and divide the resulting measure by the average standard deviation per months. The calculation of the Scaled Vol-of-Kurt is done analogously. The calculation of the Vol-of-Skew is analogously with the difference that resulting standard deviation of the twelve skewness measures is not scaled by the average skewness level per month. The distinction between the idiosyncratic and the systematic risk parts is done using a one-factor market model again. Panel E shows the summary statistics of the firm characteristics. The calculation of the cash flow variance is given in Haugen and Baker (1996), the calculation of the cash-to-assets ratio is given in Palazzo (2012), the calculation of the profit margin is given in Soliman (2008), the calculation of the share issuance follows Pontiff and Woodgate (2008), the calculation of the logarithmic stock price follows Blume and Husic (1973), the calculation of the profitability follows Fama and French (2006), the calculation of the total external financing follows Bradshaw et al. (2006) as well as the calculation of the Z-score follows Dichev (1998).

the effects of the two risk components. The calculation of the moments is based on daily returns over the respective option return period.

For the decomposition of the total moments into their idiosyncratic and their systematic part, I use the market-factor (1-F) model[29] and the following econometric model:

$$r_{i,t} = \alpha_{i,t} + \beta_i * (Mkt_t - rf_t) + \epsilon_{i,t} \tag{3.3}$$

[29]The results remain robust when the Fama and French (1993) three-factor model or the Fama and French (2015) five-factor model is used. However, the value of the systematic risk measure mechanically increases from the one-factor to the five-factor model because of the inclusion of more factors into the model. The idiosyncratic risk measure decreases accordingly with the inclusion of more factors. Additionally, also the statistical significance of the systematic risks mechanically increases in the regression analyses. I interpret this as an indication that the one-factor model best distinguishes between idiosyncratic and systematic risks and is therefore used throughout the paper.

where $r_{i,t}$ is the stock return of firm i on day t, Mkt_t is the market return and rf_t is the risk-free rate on day t. I use Kenneth French's data library to obtain the daily market factor returns. The idiosyncratic volatility is obtained by regressing the daily stock returns on the respective factor portfolio returns. Following the methodology of previous studies, I calculate the standard deviation of the residuals to obtain the idiosyncratic volatility (e.g., Cao and Han, 2013). For the idiosyncratic skewness (kurtosis), I proceed analogously in that I calculate the skewness (kurtosis) of the regression residuals.

To calculate the systematic counterpart, I calculate the moments of the time-series of the term $\beta_i * (Mkt_t - rf_t)$. The descriptive statistics of the moments as well as their idiosyncratic and systematic parts are shown in Panel C in Table 3.1. Analogously to Zhan et al. (2022) and to remove outliers, I winsorize all variables (moments, moment risks as well as firm characteristics) at the 0.5% and 99.5% levels. The values of the volatility (including the idiosyncratic and systematic part) in Table 3.1 are annualized. Panel C in Table 3.1 shows an average volatility of 47% which is comparable to existing studies (e.g., Cao and Han, 2013). Furthermore, skewness of the stock returns is close to zero with 0.15 and the kurtosis is 1.76 indicating that the stock return distributions on average are not heavily tailed. As for the idiosyncratic and the systematic parts of the moments, the idiosyncratic parts are higher with a higher dispersion for all stock return moments than their systematic counterparts. The average idiosyncratic volatility is 40% with a standard deviation of 25% while the average systematic volatility is only 20% with a standard deviation of 15%. As for the skewness, the average idiosyncratic skewness is 0.18 which is even higher than the average total skewness of 0.15. The standard deviation of the idiosyncratic skewness is 1.16 which is also higher than the dispersion of the total moment. The average systematic skewness is -0.13 with a standard deviation of 0.56. The average idiosyncratic kurtosis is 2.16 with a standard deviation of 3.89 which is also higher than the average total kurtosis. The average systematic kurtosis is 0.45 with a standard deviation of 1.23.

3.2.4 Moment Risks

The calculation of the moment risks is also based on daily returns. For every month, I calculate the respective moment of the return distribution to obtain twelve values for each stock return moment in a given year. These stock return moments are then used to calculate the moment risk using the standard deviation of the twelve values (i.e., the vol-of-vol, the vol-of-skew as well as the vol-of-kurt). From Baltussen et al. (2018), it is known that firms with a high volatility usually also exhibit a high vol-of-vol. To mitigate this problem and to better distinguish between the volatility and the vol-of-vol, I scale the vol-of-vol in a given year with the average volatility per month of that year following the methodology of Baltussen et al. (2018) and Merz and Trabert (2020). This procedure decreases the Spearman-correlation between volatility and vol-of-vol from 0.879 without scaling to 0.311 with scaling. Following the same logic, I also scale the vol-of-kurt because of its high Spearman-correlation with the kurtosis of 0.764. After scaling, the Spearman-correlation between the vol-of-kurt and the kurtosis decreases to -0.044. The vol-of-skew does not require scaling as its Spearman-correlation with the skewness is sufficiently low at 0.063.

The descriptive statistics of the moment risks are shown in Panel D of Table 3.1. The scaled vol-of-vol has a mean of 0.38 and a standard deviation of 0.17. The vol-of-skew has a mean of 0.85 with a standard deviation of 0.32. The scaled vol-of-kurt has a mean of 2.34 with a large dispersion of 12.85.

3.2.5 Firm Characteristics

The selection of firm characteristics is motivated by Zhan et al. (2022) who show that these firm characteristics are priced in delta-hedged option returns. The calculation follows the respective study that determined that they are priced in stock returns. All firm characteristics are calculated annually.

1. Cash flow variance (Haugen and Baker, 1996)[30]:

$$Cash\ Flow\ Variance = Var\left(\frac{net\ income + depreciation + amortisation}{market\ value\ of\ equity}\right)$$

2. Cash-to-assets ratio (Palazzo, 2012):

$$Cash - to - Assets\ Ratio = \frac{cash + short - term\ assets}{total\ assets}$$

[30]Haugen and Baker (1996) calculate the cash flow variance over 60 months. To ensure comparability between the firm characteristics, I calculate the cash flow variance as all other firm characteristics over 12 months. However, the results remain virtually the same if the cash flow variance is calculated over 60 months.

3. Logarithmic price (Blume and Husic, 1973): natural logarithm of the closing price at the end of the year

4. Profitability (Fama and French, 2006):

$$Profitability = \frac{income\ before\ extraordinary\ items}{book\ value\ of\ equity}$$

5. Profit margin (Soliman, 2008):

$$Profit\ Margin = \frac{EBIT}{revenues}$$

6. Share issuance 1Y (Pontiff and Woodgate, 2008):

$$Share\ Issuance\ 1Y_t = shares\ outstanding_t - shares\ ourstanding_{t-11months}$$

7. Total external financing (Bradshaw et al., 2006):

$$Total\ external\ financing = \frac{net\ share\ issuance + net\ debt\ issuance - cash\ dividends}{total\ assets}$$

8. Z-score (Dichev, 1998):

$$\begin{aligned} Z - Score = 1.2 * (&working\ capital/total\ assets) \\ &+ 1.4 * (retained\ earnings/total\ assets) \\ &+ 3.3 * (EBIT/total\ assets) \\ &+ 0.6 * (market\ value\ of\ equity/book\ value\ of\ total\ liabilities) \\ &+ (revenue/total\ assets) \end{aligned}$$

The numbers of observations range from 45,984 to 135,890. These numbers are considerably lower than those of Zhan et al. (2022). The reason is that I report firm-year observations while Zhan et al. (2022) show firm-month observations which explains the differences in numbers of observations.

3.3 Empirical Results

3.3.1 Exposure to Stock Return Moments

As a starting point for my analyses, I study the exposure of realized delta-hedged option returns to the second, third and fourth stock return moment of the respective underlying. To study this relationship, I regress the delta-hedged option returns on the volatility, the skewness as well as the kurtosis of the underlying's return distribution using fixed effects regressions with time fixed effects. The moments are measured over the period of the respective option return to ensure the exposure measurement. Additionally, to isolate the effect of the respective moment without disturbing effects from the other moments, I orthogonalize all three moments. Table 3.2 shows the regression coefficients and Newey and West (1987) t-statistics in brackets.[31]

Table 3.2: FE-Regression of DH-Returns on Orthogonalized Stock Return Moments

	Dependent variable:	
	DH Call Returns	DH Put Returns
	(1)	(2)
Volatility	1.432***	1.182***
	(26.928)	(27.925)
Skewness	−0.005***	−0.004***
	(−13.082)	(−10.732)
Kurtosis	0.006***	0.005***
	(47.719)	(53.250)
Significance levels:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows fixed effects regressions of delta-hedged option returns on volatility, skewness and kurtosis including time fixed effects. The stock return moments are estimated from daily stock return over the respective option return period. The reported t-statistics are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

The results show that delta-hedged option portfolios have clear exposure to all three moments of which the coefficients for volatility and kurtosis are positive and the coefficient for skewness is negative. All coefficients are highly significant with t-statistics ranging

[31] The estimation of autocorrelation- and heteroskedasticity robust standard errors in panel data uses a variant of the standard Newey and West (1987) estimator. For more details, see, for example, Petersen (2009).

(in absolute terms) from 13.082 to 47.719 for calls and from 10.732 to 53.250 for puts. Economically, a one standard deviation increase is associated c.p. with a percentage point increase of the delta-hedged option returns of 2.5% $(= 1.432 * (0.28/\sqrt{252}))$[32] for calls and 2.1% $(= 1.182 * (0.28/\sqrt{252}))$ for puts. A one standard deviation increase of skewness is associated c.p. with a percentage point decrease of delta-hegded option returns of -0.5% for calls and -0.4% for puts. Moreover, a one standard deviation increase of kurtosis is associated with option return increases (in percentage points) of 2.1% for calls and 1.8% for puts.

The signs of the coefficients for the different moments are to be interpreted in that delta-hedged option returns increase when the even moments (i.e., volatility and kurtosis) increase and when the third moment (i.e., skewness) decreases. In other words, delta-hedged option portfolio serve as an insurance against volatility and kurtosis increases as well as skewness decreases. This is consistent with the argument of Bakshi and Kapadia (2003a,b) that options serve as a hedge against the leverage effect where stock price downfalls coincide with volatility rises. Further, they also hedge against skewness declines and kurtosis increases. They are therefore compatible with investors' aversion against even moments and investors' preference for higher skewness (e.g., Dittmar, 2002; Litzenberger and Kraus, 2016).[33]

To shed more light on the question whether delta-hedged option returns have exposure to mainly the idiosyncratic or the systematic risks (or both), I repeat the analysis with both risk parts of the moments. Table 3.3 shows the results.

Again, volatility is associated with the largest changes in realized option returns due to a one standard deviation shock compared to the higher moments. The association of a one standard deviation increase of idiosyncratic volatility with realized delta-hedged option returns is in percentage points 2.6% for calls and 2.2% for puts compared to 2.0% for calls and 1.9% for puts for the systematic volatility. A one standard deviation increase in the idiosyncratic skewness as well as kurtosis are associated with considerably lower realized option return increases. As for the skewness it is associated c.p. with an increase in percentage points of realized delta-hedged option returns of -0.6% for calls and -0.4%

[32] Note that the volatility measures in Table 3.1 are annualized.

[33] Unreported results show that these results remain virtually the same in crisis- and non-crisis periods.

for puts. As for the kurtosis, is it associated with an increase of 2.0% for calls and 1.6% for puts. The association of a one standard deviation shock in the systematic part of the third and fourth moment is even lower in percentage points with -0.2% for the systematic skewness (calls and puts) as well as 0.1% (calls) and 0.2% (puts) for the systematic kurtosis. All coefficients show the same sign as in Table 3.2 for both the idiosyncratic and the systematic part of the respective stock return moment.

Table 3.3: FE-Regression of DH-Returns on Orthogonalized Idiosyncratic and Systematic Stock Return Moments

	Dependent variable:	
	DH Call Returns	DH Put Returns
	(1)	(2)
IdioVol	1.637***	1.391***
	(12.585)	(10.926)
SysVol	1.937*	1.899*
	(1.740)	(1.856)
IdioSkew	−0.005***	−0.003***
	(−10.108)	(−8.067)
SysSkew	−0.003	−0.003
	(−0.799)	(−0.899)
IdioKurt	0.005***	0.004***
	(17.303)	(15.584)
SysKurt	0.001	0.002
	(0.181)	(0.620)
Significance levels:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows fixed effects regressions of delta-hedged option returns on volatility, skewness and kurtosis including time fixed effects. The stock return moments are estimated using daily stock returns over the respective option return period. To distinguish between the idiosyncratic and systematic risk part of the moments, I use a one-factor the market model. The factor returns were obtained from Kenneth French's homepage. The reported t-statistics are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

Interestingly, the results show that mainly the idiosyncratic parts are driving the exposure of delta-hedged option returns. The idiosyncratic part of all moments are highly significant with Newey and West (1987) t-statistics between 8.067 and 17.303 in absolute terms. With exception of the systematic volatility, none of the systematic moment parts have significant coefficients. Even the systematic volatility is only just significant on the 10%

level with Newey and West (1987) t-statistics of 1.740 for calls and 1.856 for puts.[34] In summary, delta-hedged option returns serve as insurances mainly against the idiosyncratic part of the third and fourth moment. As for the volatility, delta-hedged option portfolios hedge against increases of the idiosyncratic and additionally against systematic volatility increases in times of crises. But from a statistical point of view, the idiosyncratic volatility has a much higher significance.

3.3.2 Exposure to Moment Risks

It is known from recent studies that not only the volatility but also the vol-of-vol (i.e. variance risk) is priced in delta-hedged option returns (e.g., Cao et al., 2019; Ruan, 2020). Hence, it is sensible to study whether delta-hedged option portfolios also have exposure to variance risk. For this purpose, I regress the delta-hedged option return on the annual scaled vol-of-vol. A common argument for the pricing of variance risk is the ambiguity aversion because a high vol-of-vol reflects a higher uncertainty about risk for which investors demand compensation (Ellsberg, 1961; Baltussen et al., 2018). Following this reason, it stands to reason that investors also demand compensation for moment risks of higher moments such as the skewness and kurtosis. Hence, it is sensible to extend the analysis by the higher moment risks to analyze whether delta-hedged option portfolios have exposure to them too. I include the vol-of-skew and vol-of-kurt to shed more light on the exposure of delta-hedged option returns to all moment risks. Because moment risks are annual measures, I calculate the average delta-hedged option return per firm per year and regress these yearly delta-hedged option returns on the moment risk measures using time fixed-effects regressions. Table 3.4 shows the results for the total moment risks.

The results show that delta-hedged option portfolios have exposure to variance risk as well as to skewness risk but not to kurtosis risk. The coefficients for scaled vol-of-vol and vol-of-skew are both positive and highly significant with Newey and West (1987) t-statistics ranging from 6.519 to 7.241. This means that delta-hedged option returns positively correlate with variance risk and skewness risk increases. Economically, a one standard deviation increase of the scaled vol-of-vol is associated c.p. with an increase in percentage

[34]Unreported results show that this result is driven by times of crises (I define the crisis periods analogous to Chapter 2 as June 2007 to December 2009 (GFC) and January 2020 to June 2021 (COVID-19)). The coefficient for the systematic volatility loses its significance once the observations from crisis periods are removed. The other results of crisis- and non-crisis periods remain virtually the same as the results of the total sample period.

Table 3.4: FE-Regression of DH-Returns on Orthogonalised Total Moment Risks

	Dependent variable:	
	DH Call Returns	DH Put Returns
	(1)	(2)
Scaled Vol-of-Vol	0.038***	0.032***
	(6.946)	(7.149)
Vol-of-Skew	0.012***	0.011***
	(6.519)	(7.241)
Scaled Vol-of-Kurt	−0.00003	−0.00001
	(−1.561)	(−0.312)
Significance levels:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows fixed effects regressions of delta-hedged option returns on variance risk (vol-of-vol), skewness risk (vol-of-skew) and kurtosis risk (vol-of-kurt) including time fixed effects. For every month, the stock return moments are estimated using daily stock return data. The respective moment risk is then calculated estimating the standard deviation of the twelve stock return moment estimations per year. Because the even moments (i.e., volatility and kurtosis) show a high correlation with their moment risk, the moment risks are scaled by the average stock return moment per month over the year following the methodology by Baltussen et al. (2018). The reported t-statistics are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

points of realized delta-hedged option returns of 0.6% for calls and 0.5% for puts. Such an increase in skewness risk is associated c.p. with a percentage point increase in realized delta-hedged option returns of 0.4% for both calls and puts. Delta-hedged option portfolios therefore hedge against increases of volatility uncertainty as well as skewness uncertainty but not against kurtosis uncertainty. The results for scaled vol-of-vol are consistent with the findings of Cao et al. (2019) and Ruan (2020) who show that variance risk is driving expected delta-hedged option returns. Both studies show a negative relationship between historic vol-of-vol and expected delta-hedged option returns. Therefore, my results are consistent with the explanation that investors are paying a premium to be hedged against variance risk because options do hedge against the variance risk and additionally against the skewness risk.[35]

[35]Unreported results show that this insurance only applies to non-crisis periods as all coefficients lose significance in times of crisis.

Because of the importance of the idiosyncratic stock return moments, I study the exposure to the idiosyncratic and systematic parts of the moment risks as well. Table 3.5 shows the results of the fixed-effects regressions using time fixed effects.

As expected, only the coefficients for the variance risk parts and for the skewness risk parts are significant with exception of the coefficient for idiosyncratic vol-of-kurt for puts. But this coefficient is only just significant on the 10%-level with a Newey and West (1987) t-statistic of -1.710. As for the other coefficients, they are all significant on the 5%- or even 1%-level. Interestingly, the coefficients for the idiosyncratic and systematic parts do not show the same signs for the respective moment risk. The coefficients of the idiosyncratic vol-of-vol as well as the idiosyncratic vol-of-skew are positive while their systematic counterparts show negative signs. Therefore, delta-hedged option portfolios serve as an insurance against increases of the idiosyncratic moment risks of the second and third moment and against decreases of the respective systematic moment risks. Although both the idiosyncratic as well as the systematic parts are highly significant, the idiosyncratic parts show Newey and West (1987) t-statistics which are twice as high for the variance risk and even three times as high for the skewness risk.[36]

Economically, the association (in percentage points) with a one standard deviation increase of the variance risk c.p. is for the idiosyncratic vol-of-vol 0.8% for calls and 0.6% for puts while it is -0.5% for calls and -0.4% for puts for the systematic counterpart. As for skewness risk, a one standard deviation increase in the idiosyncratic vol-of-skew is associated c.p. with an increase of realized delta-hedged option return (in percentage points) of 0.4% for calls and 0.3% for puts. The association with the systematic counterpart is -1.0% for calls and 0.8% for puts. Interestingly, Cao et al. (2019) show that both risk parts of the variance risk carry a negative price (i.e. investors pay a premium for high vol-of-vol options regardless of whether the idiosyncratic or the systematic variance risk is high). My findings show that this premium is only justified for the idiosyncratic variance risk because options serve against idiosyncratic variance risk increases but not against systematic variance risk

[36] As unreported results show, is the significant coefficient of the idiosyncratic skewness risk driven by observations of non-crisis periods while the result for the systematic skewness risk is driven by observations of crisis periods. Hence, the coefficient of the systematic skewness risk loses its significance in non-crisis periods while the coefficient for the idiosyncratic skewness risk is insignificant in times of crisis. The other results of crisis- and non-crisis periods remain virtually unchanged to the results of the total sample period.

Table 3.5: FE-Regression of DH-Returns on Orthogonalised Idiosyncratic and Systematic Moment Risks

	Dependent variable:	
	DH Call Returns	DH Put Returns
	(1)	(2)
IdioVol-of-Vol	0.042***	0.036***
	(9.935)	(10.484)
SysVol-of-Vol	−0.023***	−0.019***
	(−5.304)	(−6.973)
IdioVol-of-Skew	0.011***	0.009***
	(6.717)	(6.919)
SysVol-of-Skew	−0.053**	−0.047**
	(−2.211)	(−2.549)
IdioVol-of-Kurt	−0.00003	−0.00003*
	(−1.429)	(−1.710)
SysVol-of-Kurt	−0.00004	−0.0001
	(−0.209)	(−0.423)
Significance levels:	*p<0.1; **p<0.05; ***p<0.01	

Note: This table shows fixed effects regressions of delta-hedged option returns on variance risk (vol-of-vol), skewness risk (vol-of-skew) and kurtosis risk (vol-of-kurt) including time fixed effects. For every month, the stock return moments are estimated using daily stock return data. The respective moment risk is then calculated estimating the standard deviation of the twelve stock return moment estimations per year. Because the even moments (i.e., volatility and kurtosis) show a high correlation with their moment risk, the moment risks are scaled by the average moment over the year following the methodology by Baltussen et al. (2018). To distinguish between the idiosyncratic and systematic risk part of the moment risks, I use a one-factor the market model. The factor returns were obtained from Kenneth French's homepage. The reported t-statistics are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

increases. For the systematic variance risk, options serve as a hedge against systematic risk uncertainty decreases.

3.3.3 Exposure to Firm Characteristics

In this section, I study the exposure of delta-hedged option portfolios to firm characteristics. Zhan et al. (2022) show that several firm characteristics are priced in option returns and that these pricing effects cannot be explained by common risk factors. Since these firm characteristics are priced, I aim to shed more light on the exposures of delta-hedged portfolios to them. To study the exposures, I use single sorts and build a long-short strategy on them which buys the options on stocks with a high exhibition of the respective firm characteristic and sells options on stocks with a low exhibition of the respective firm characteristic. For every year, I sort the annual average delta-hedged option returns by the respective firm characteristic and build quintiles. I then calculate the time-series averages of every quintile portfolio as well as the average return of the long-short strategy based on these quintiles. Table 3.6 shows the time-series averages of the long-short strategy for all firm characteristics in my study with Newey and West (1987) t-statistics in brackets.

Table 3.6: Average Returns of a Long-Short Strategy build on Single Sorts based on Firm Characteristics

	DH Call Returns	DH Put Returns
Cash Flow Variance	-0.130% (-0.801)	-0.120% (-0.962)
Cash-to-Assets Ratio	$-1.300\%^{***}$ (-3.167)	$-0.890\%^{***}$ (-3.053)
Ln(Price)	$2.570\%^{***}$ (4.454)	$1.840\%^{***}$ (4.970)
Profitability	$1.440\%^{***}$ (3.944)	$1.070\%^{***}$ (4.083)
Profit Margin	$1.370\%^{***}$ (3.488)	$1.040\%^{***}$ (3.665)
Share Issuance 1Y	$-0.740\%^{*}$ (-1.962)	$-0.630\%^{**}$ (-2.235)
Total External Financing	0.010% (0.060)	-0.010% (0.127)
Z-Score	$0.770\%^{**}$ (2.738)	$0.580\%^{**}$ (2.762)
Significance levels:		*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns of a long-short strategy (5-1) that buys the options in the highest firm characteristic quantile and sells the options in the lowest firm characteristic quantile. It shows the average returns of the long-short strategy each built on Haugen and Baker's (1996) cash flow variance, Palazzos's (2012) cash-to-assets ratio, Blume and Husic's (1973) logarithmic stock price, Fama and French's (2006) profitability, Soliman's (2008) profit margin, Pontiff and Woodgate's (2008) share issuance over one year, Bradshaw et al.'s (2006) total external financing as well as Dichev's (1998) Z-score. The reported t-statistics are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

Almost all firm characteristics show highly significant average returns of the long-short strategy. The exceptions are the cash flow variance and the total external financing which are not significant.[37] The results therefore show that delta-hedged option portfolios have exposure to the cash-to-assets ratio, the logarithmic closing price at the end of the year, the profitability as well as the profit margin of the underlying, the share issuance and the Z-score. The average long-short returns based on the cash-to-assets ratio and the share issuance show a negative sign while the exposure to the rest of the (significant) firm characteristics is positive. These signs are the same as in Zhan et al. (2022).

Delta-hedged option returns therefore decrease with increasing cash-to-assets ratio and share issuance as well as increase with the logarithmic share price, profitability, profit margin and the Z-score. Palazzo (2012) argues that firms with riskier cash flows (i.e. riskier firms) have higher cash holdings as precautionary savings. Following this logic, if firms now experience an increase in their riskiness and therefore in their cash-to-assets ratio, delta-hedged option returns decrease which is unexpected as options serve well as insurances against increases of risks measured by the stock return moments (s. Section 3.3.1). The negative sign is also found by Zhan et al. (2022).[38] Given that firms with a higher cash-to-assets ratio are riskier, investors pay a premium for options on riskier firms (analogous to high vol-of-vol options). But in contrast to the variance risk, options do not hedge against increases in cash-to-assets ratio which makes the pricing seem questionable. An analysis of the triangular relationship between delta-hedged option returns, cash-to-assets ratio and the stock return moments will shed more light on this puzzle and is presented in the next section.

As for the logarithmic stock price, table 3.6 shows a positive average return of the long-short strategy suggesting a positive exposure of delta-hedged option returns to the price of the underlying. This significant exposure is particularly interesting as the linear effect of the stock (i.e., the stock return) on the option return is hedged away and only non-linear effects remain. Blume and Husic (1973) argue that the stock price is in part an indicator

[37]Unreported results show that the average return of the long-short strategy built on the cash flow variance becomes significantly negative in non-crisis periods only (for both calls and puts). The average return of the strategy built on the total external financing on the other hand becomes significantly negative for calls in times of crisis only. The other results of crisis- and non-crisis periods remain virtually the same as the results of the total sample period.

[38]Note that Zhan et al. (2022) analyze portfolios of delta-hedged call writings whereas I analyze portfolios in which the investor is long in the option. Hence, all signs of the sorting analysis in Zhan et al. (2022) must be reversed to make the results comparable to mine.

for changes in a stock's risk level because of its association with changes in future beta. Beta measures the sensitivity of the stock to systematic risk. If the price serves as a proxy for the true beta, it serves as a proxy for the true sensitivity of the underlying to a systematic factor. This is consistent with my results because delta-hedged option portfolios have exposure to systematic volatility as shown in Table 3.3. My results are therefore consistent the explanation that the stock price acts as an indicator of a firm's risk, against which options serve as an insurance.

Further, delta-hedged option returns show a positive association with profitability. Following the argument of Fama and French (2006) that more profitable firms are more risky, delta-hedged options hedge against this risk.

Another firm characteristic that delta-hedged option returns have a positive exposure to is the profit margin. The profit margin is found to be positively associated with contemporaneous stock returns (Soliman, 2008). Further, it is also shown to be negatively associated with idiosyncratic risk (Brown and Kapadia, 2007; Adjei and Adjei, 2017). However, Brown and Kapadia (2007) argue that this association is due to developments of stock market listings in the post-war era. New listings of riskier firms explain the association between the profit margin and idiosyncratic risks. Hence, it is questionable whether the correlation between profit margin and idiosyncratic risk actually exists or whether this is just a spurious relationship. As shown in Section 3.3.1, delta-hedged option portfolios hedge especially against idiosyncratic risks. Hence, the finding of a positive coefficient of the profit margin in Table 3.6 is not consistent with the finding of the literature that the profit margin is negatively correlated with idiosyncratic risk. My results instead suggest that the profit margin is positively associated with the riskiness of a firm.

The share issuance, on the other hand, is a firm characteristic that delta-hedged option postfolios have a negative exposure to. It has also a negative association with future stock return as shown by Pontiff and Woodgate (2008). Even though the authors conclude it is unlikely that the issuance effect can be explained by a risk-based explanation, my results suggest that it does have an effect on a stock that goes beyond the mean of the stock return. Because realized delta-hedged option returns react to non-linearity (because the linear effect of the stock return is hedged away), this suggests that the share issuance affects the riskiness of the firm.

The Z-score measures the probability of bankruptcy of a firm (Dichev, 1998). A higher Z-score thereby indicates a lower default risk. Hence, the positive sign of the coefficient of the Z-score in table 3.6 is surprising as delta-hedged option returns decrease with higher default risk and do not serve as an insurance against bankruptcy risk. The positive sign again resembles that in Zhan et al. (2022) as well as in Vasquez and Xiao (2020) who find that expected delta-hedged option returns decrease with higher default risk. Vasquez and Xiao (2020) argue in a compound option model that investors are willing to pay a premium to be hedged against higher variance risk caused by a higher default risk. My results, however, show that options do not serve as a hedge against bankruptcy risk increases. They hedge against variance risk increases but not against increasing default risk.

3.3.4 The Moderating Effects of Stock Return Moments

In this section, I study the triangular relationship between delta-hedged option returns, firm characteristics and the idiosyncratic stock return moments. As realized delta-hedged option returns have exposure to firm characteristics and because firm characteristics are known to indicate a firm's riskiness (e.g., Palazzo, 2012), I aim to shed light on the interaction between firm characteristics and the idiosyncratic stock return moments in their association with realized delta-hedged option returns. I use the idiosyncratic instead of the total stock return moments because as shown in Section 3.3.1, delta-hedged option portfolios have exposure to especially idiosyncratic risks. So I argue that any effect of the total stock return moment on the relationship between firm characteristic and realized delta-hedged option return will be driven by the idiosyncratic part of the stock return moments.[39] This sheds light on the question whether firm characteristics reflect the same risks as the stock return moments or whether they provide additional information about the riskiness of a firm. To investigate this triangular relationship, I use double sorts. For every year, I first sort all delta-hedged option returns by the respective firm characteristic and build quintiles. Within each quintile, I sort the delta-hedged option returns again by the respective stock return moment. Additionally, I also calculate the returns of a long-short strategy that buy options written on stocks with a high exhibition of the firm characteristic and sells the options on stocks with a low exhibition of the firm characteristic. As I repeat this calculation every year, I calculate the time-series average as well as the Newey and

[39]Unreported results show that the results remain virtually the same when the total stock return moments are used instead of the idiosyncratic moments.

West (1987) t-statistics of the returns of the difference-portfolios. Table 3.7 shows the average returns of the long-short strategy built on firm characteristics for different levels of annual idiosyncratic volatility.

Table 3.7: Average Returns of a Long-Short Strategy Built on Firm Characteristics for Different Levels of Annual Idiosyncratic Volatility

	Annual Idiosyncratic Volatility					
	1-low	2	3	4	5-high	5-1
Cash Flow Variance	−0.490%** (−1.761)	−0.110% (−0.923)	−0.100% (−0.378)	0.240% (0.690)	−0.150% (−0.598)	0.340% (0.854)
Cash-to-Assets Ratio	−0.390%*** (−3.575)	−1.080%*** (−5.430)	−1.470%*** (−3.313)	−2.090%*** (−3.215)	−1.260% (−1.389)	−0.870% (−0.930)
Ln(Price)	2.240%*** (8.863)	2.790%*** (5.785)	2.570%*** (5.708)	2.450%*** (4.377)	2.540%** (2.186)	0.300% (0.306)
Profitability	1.130%*** (6.985)	1.960%*** (7.633)	2.060%*** (4.633)	1.750%*** (2.933)	0.610% (0.727)	−0.520% (−0.625)
Profit Margin	1.020%*** (7.532)	1.500%*** (5.427)	1.200%*** (4.565)	1.550%*** (3.352)	1.040% (0.999)	0.020% (0.021)
Share Issuance 1Y	−0.080% (−0.591)	−0.310%** (−2.170)	−0.620%** (−1.987)	−1.270%** (−2.061)	−1.130% (−1.610)	−1.050%* (−1.740)
Total External Financing	−0.020% (−0.264)	0.080% (0.699)	0.220% (1.272)	−0.070% (−0.317)	−0.230% (−0.630)	−0.210% (−0.517)
Z-Score	0.070% (0.401)	0.580%** (2.009)	0.850%** (2.409)	1.410%*** (5.280)	−0.240% (−0.401)	−0.310% (−0.558)
Significance levels:						*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns of a long-short strategy (5-1) that buys the options in the highest firm characteristic quantile and sells the options in the lowest firm characteristic quantile for different levels of idiosyncratic volatility. It shows the average returns of the long-short strategy each built on Haugen and Baker's (1996) cash flow variance, Palazzos's (2012) cash-to-assets ratio, Blume and Husic's (1973) logarithmic stock price, Fama and French's (2006) profitability, Soliman's (2008) profit margin, Pontiff and Woodgate's (2008) share issuance over one year, Bradshaw et al.'s (2006) total external financing as well as Dichev's (1998) Z-score. The volatility is estimated as the standard deviation of daily stock returns over one year. To distinguish between the idiosyncratic and the systematic risk part, I use a one-factor market model. The factor returns are obtained from Kenneth French's data library. The reported t-statistics in parentheses are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

The last column ('5-1') shows the average return of a long-short strategy that buys options where annual idiosyncratic volatility is high and sells options where annual idiosyncratic volatility is low. If the idiosyncratic volatility were to have a moderating effect on the relationship between firm characteristics and delta-hedged option returns, these average returns would be economically and statistically significant. However, none of the average returns in the last column are significant. Although the annual idiosyncratic volatility does not appear to have a moderating effect on the magnitude of the returns of the difference-portfolios, it does have an effect on the statistical significance. The average returns of a long-short strategy built on firm characteristics show the highest t-statistics when annual idiosyncratic volatility is low and are only slightly significant (or not significant at all) when annual idiosyncratic volatility is high. With exception of the share issuance and the total external financing, all firm characteristics show a mostly monotonic decrease of the statistical significance from the low-volatility quintile to the high-volatility quintile.[40] Even the cash flow variance, which does not appear to have a significant association with realized delta-hedged option returns in the single sort, has a significantly negative relationship with realized delta-hedged option returns when annual idiosyncratic volatility is low.

Next, I study the triangular relationship between realized delta-hedged option returns, firm characteristics and annual idiosyncratic skewness. Table 3.8 shows the average returns of the long-short strategy built firm characteristics for different levels of idioyncratic skewness.

In contrast to the results with annual idiosyncratic volatility, the annual idiosyncratic skewness appears to have a moderating effect on the relationship between firm characteristics and delta-hedged option returns because all average returns of the long-short strategy of the difference-portfolios are significant with one exception, the total external financing.[41] Interestingly, now the relationship between firm characteristics and realized delta-hedged option returns is more pronounced when idiosyncratic skewness is high (both economically and statistically).

Lastly, I repeat the analysis with annual idiosyncratic kurtosis. Table 3.9 shows the results. These results are rather diverse. For some firm characteristics (profit margin, share issuance as well as the logarithmic stock price), the annual idiosyncratic kurtosis appears to have a moderating effect on the relationship between firm characteristics and realized

[40] As unreported results show, consistent with the significantly negative average return for the total external financing in the single sort in times of crisis, the difference-portfolio ('5-1') shows a significantly negative return in the double sort in times of crisis as well. The other results of crisis- and non-crisis periods remain virtually the same as the results of the total sample period.

[41] Unreported results show that the average return of the difference-portfolio ('5-1') built on the total external financing becomes significantly negative in times of crisis while the difference-portfolios ('5-1') built on the cash flow variance, the profitability, the profit margin, the share issuance and the Z-score become insignificant in crisis periods. The other results of the crisis- and non-crisis periods remain virtually the same as the results of the total sample period.

Table 3.8: Average Returns of a Long-Short Strategy Built on Firm Characteristics for Different Levels of Annual Idiosyncratic Skewness

	Annual Idiosyncratic Skewness					
	1-low	2	3	4	5-high	5-1
Cash Flow Variance	0.080%	0.190%	−0.100%	−0.430%**	−0.360%	−0.440%***
	(0.402)	(1.139)	(−0.514)	(−2.188)	(−1.322)	(−3.178)
Cash-to-Assets Ratio	−0.220%	−0.920%**	−1.410%***	−1.870%***	−1.900%***	−1.680%***
	(−0.562)	(−2.427)	(−2.866)	(−2.819)	(−3.843)	(−5.112)
Ln(Price)	0.230%	1.970%***	3.030%***	3.870%***	3.570%***	3.340%***
	(0.448)	(5.147)	(4.688)	(4.703)	(6.461)	(17.371)
Profitability	0.210%	1.260%***	1.780%***	2.470%***	2.040%***	1.830%***
	(0.883)	(3.232)	(3.902)	(3.147)	(3.936)	(4.631)
Profit Margin	−0.020%	1.150%***	1.580%***	2.480%**	1.330%***	1.350%***
	(−0.061)	(3.252)	(5.770)	(2.227)	(7.253)	(4.073)
Share Issuance 1Y	−0.290%	−0.520%**	−0.620%	−0.890%*	−1.100%***	−0.810%***
	(−0.788)	(−2.153)	(−1.534)	(−1.746)	(−3.000)	(−3.570)
Total External Financing	0.020%	−0.230%	−0.140%	0.120%	0.200%	0.190%
	(0.105)	(−1.433)	(−0.719)	(0.712)	(0.819)	(0.789)
Z-Score	0.010%	0.170%	0.060%	1.190%***	1.220%***	1.210%***
	(0.045)	(0.559)	(0.197)	(3.067)	(3.807)	(3.651)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns of a long-short strategy (5-1) that buys the options in the highest firm characteristic quantile and sells the options in the lowest firm characteristic quantile for different levels of idiosyncratic volatility. It shows the average returns of the long-short strategy each built on Haugen and Baker's (1996) cash flow variance, Palazzos's (2012) cash-to-assets ratio, Blume and Husic's (1973) logarithmic stock price, Fama and French's (2006) profitability, Soliman's (2008) profit margin, Pontiff and Woodgate's (2008) share issuance over one year, Bradshaw et al.'s (2006) total external financing as well as Dichev's (1998) Z-score. The skewness is estimated as the skewness of daily stock returns over one year. To distinguish between the idiosyncratic and the systematic risk part, I use a one-factor market model. The factor returns are obtained from Kenneth French's data library. The reported t-statistics in parentheses are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

delta-hedged option returns. As shown in the last column ('5-1'), the long-short strategy of the difference-portfolios yield negative average returns with -1.640% for the profit margin, -0.410% for the share issuance and -1.390% for the logarithmic share price. Note that the relationships between realized delta-hedged option returns and the logarithmic stock price as well as the profit margin are both positive while the relationship between realized delta-hedged option returns and the share issuance are negative in the single sort (s. Table 3.6). Hence, the relationship between delta-hedged option returns and the logarithmic stock price as well as the profit margin is more pronounced when annual idiosyncratic kurtosis is low. As for the share issuance, the moderating effect is reversed and the relationship between realized delta-hedged option returns and share issuance is more pronounced when annual idiosyncratic kurtosis is high. For the other firm characteristics (cash flow variance, cash-to-assets ratio, profitability, total external financing as well as the Z-score), the relationships with realized delta-hedged option returns tend to be more pronounced when annual idiosyncratic kurtosis is low although the long-short strategy built on these difference-portfolios do not show significant average returns.[42] However, the long-short strategies built on sorts of the cash-to-assets ratio, the profitability as well as the total external financing show average returns that are generally increasing in significance with decreasing annual idiosyncratic kurtosis and have highly significant average returns when annual idiosyncratic kurtosis is low.

In summary, the double sorts give interesting insights into the the triangular relationship between realized delta-hedged option returns, firm characteristics and the idiosyncratic stock return moments. While the relationship between delta-hedged option returns is generally more informative when the even moments are low[43], this moderating effect is reversed with annual idiosyncratic skewness. Here, the relationships between realized delta-hedged option returns and firm characteristics are more informative when annual idiosyncratic skewness is high. This suggests that firm characteristics provide additional information especially when the moments indicate a low risk of the underlying. This could be an expression of the peso problem. Option returns are driven by risks which are unobservable. So, the question arises how to appropriately measure risk. If the stock return happens to exhibit a rather quiet path, the stock return moments do not reflect the whole picture of a firm's riskiness. Additionally, with exception of the cash flow variance, firm characteristics are point estimators while the return distribution moments are period estimators. So the firm characteristics might contain additional information about the riskiness of the underlying at the point in time because the moments contain information of random low-risk periods. The firm characteristics as alternative risk measures thereby

[42] Unreported results show that the average return of the difference-portfolio ('5-1') built on the cash flow variance becomes significantly negative in non-crisis periods (consistent with the single-sort results) with the most significant return in the low-kurtosis quintile. The other results of crisis- and non-crisis periods remain virtually the same as the results of the total sample period.

[43] With exception of the share issuance which has a stronger association with delta-hedged option returns when annual idiosyncratic kurtosis is high.

Table 3.9: Average Returns of a Long-Short Strategy Built on Firm Characteristics for Different Levels of Annual Idiosyncratic Kurtosis

	Annual Idiosyncratic Kurtosis					
	1-low	2	3	4	5-high	5-1
Cash Flow Variance	0.000%	−0.400%	−0.300%	0.230%	−0.110%	−0.120%
	(0.013)	(−1.455)	(−1.527)	(1.206)	(−0.370)	(−0.474)
Cash-to-Assets Ratio	−1.420%***	−1.620%***	−1.260%**	−1.190%***	−0.790%*	0.640%
	(−2.690)	(−3.553)	(−2.420)	(−3.319)	(−1.710)	(1.143)
Ln(Price)	2.960%***	3.350%***	2.450%***	2.640%***	1.340%*	−1.620%***
	(8.586)	(5.221)	(4.765)	(3.236)	(1.934)	(−3.751)
Profitability	1.840%***	1.750%***	1.680%***	1.510%***	0.750%	−1.090%*
	(6.117)	(4.079)	(3.505)	(4.611)	(1.140)	(−1.716)
Profit Margin	1.680%***	2.000%***	1.370%***	1.530%*	−0.050%	−1.730%***
	(5.428)	(2.915)	(3.538)	(1.900)	(−0.210)	(−6.613)
Share Issuance 1Y	−0.350%	−0.710%*	−1.000%**	−0.600%*	−0.750%*	−0.400%***
	(−1.051)	(−1.856)	(−2.235)	(−1.918)	(−1.919)	(−2.460)
Total External Financing	−0.120%	0.150%	0.240%	−0.100%	−0.190%	−0.070%
	(−1.173)	(0.936)	(1.438)	(−0.682)	(−0.742)	(−0.298)
Z-Score	0.120%	0.500%	0.940%***	0.850%***	0.190%	0.070%
	(0.292)	(1.642)	(2.685)	(2.903)	(0.439)	(0.157)

Significance levels: *p<0.1; **p<0.05; ***p<0.01

Note: This table shows the average returns of a long-short strategy (5-1) that buys the options in the highest firm characteristic quantile and sells the options in the lowest firm characteristic quantile for different levels of idiosyncratic volatility. It shows the average returns of the long-short strategy each built on Haugen and Baker's (1996) cash flow variance, Palazzos's (2012) cash-to-assets ratio, Blume and Husic's (1973) logarithmic stock price, Fama and French's (2006) profitability, Soliman's (2008) profit margin, Pontiff and Woodgate's (2008) share issuance over one year, Bradshaw et al.'s (2006) total external financing as well as Dichev's (1998) Z-score. The kurtosis is estimated as the kurtosis of daily stock returns over one year. To distinguish between the idiosyncratic and the systematic risk part, I use a one-factor market model. The factor returns are obtained from Kenneth French's data library. The reported t-statistics in parentheses are corrected for autocorrelation and heteroskedasticity following Newey and West (1987).

complement the stock return moments by adding more information about the actual riskiness of the company.

3.4 Conclusion

I study delta-hedged option portfolios using a large data set of options on 7,320 different stocks over the period from January 1996 to June 2021. My results show that realized delta-hedged option returns have exposure to the volatility, the skewness as well as the kurtosis and that especially the idiosyncratic risk parts of these moments are driving these exposures. This highlights the importance of idiosyncratic risks for equity option returns. Further, also the moment risk of the volatility as well as the skewness affect realized delta-hedged option returns. In the case of moment risks, however, both the idiosyncratic and the systematic parts are significant with different signs even though the idiosyncratic moment risks show higher statistical significance. Moreover, I show that also firm characteristics affect realized delta-hedged option returns. However, delta-hedged option portfolios do not show exposure to all firm characteristics that are shown by Zhan et al. (2022) to be priced in expected delta-hedged option returns. This raises the question why the firm characteristics are priced in expected delta-hedged option returns. An analysis of the triangular relationships between realized delta-hedged option returns, firm characteristics and the stock return moments shows that the exposure to firm characteristics is especially informative when the moments indicate low risk of the underlying stock. I interpret this finding as an example of a peso problem in which the moments indicate low risk, however, this is not an accurate representation of the true riskiness of the firm. In this case, the firm characteristics serve as alternative risk measures that provide further information about the true riskiness of the underlying.

However, there is still need for a better understanding of the cross-section of delta-hedged option returns. An analysis of the different effects of upside- versus downside risks might be interesting to learn more about the effects of negative versus positive return variations. But I leave this to future research. Additionally, further analyses of the exposures of realized delta-hedged option portfolios to firm characteristics might bring more interesting insights into the economic channels through which firm characteristics affect realized delta-hedged option returns.

4 A Tale Of Two Crises Told by Options

Joint work with Olaf Korn.

Abstract

This paper retells the story of two crises, the Global Financial Crisis and the Covid pandemic, from the perspective of market expectation contained in option prices. Using options with different strike prices and times-to-maturity, we construct risk-neutral densities for different time horizons. Our results show both similarities and differences between the two crises. In particular, the use of risk-neutral densities offers a look at specific events and decisions during the crises that goes beyond stock price reactions or risk-neutral variance and skewness. We also ask whether new post-crisis regimes were visible after the massive systemic shocks of the crises.

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4.1 Introduction

Financial markets serve different purposes. One of them is the aggregation of information. The reaction of asset prices shows how certain events and policy measures are perceived with respect to their economic effects. A current example is the announcement of tax cuts and increased spending by the British government. Both FX and government bond markets reacted massively, the Bank of England had to intervene and the announced tax cuts were finally withdrawn. Especially in times of crisis, information reflected in asset prices can be of particular importance for preventing misjudgments.

This paper uses information from option prices to obtain a better understanding of crises. In particular, we look at two systemic crises, the Global Financial Crisis (GFC)[44] and the COVID-19 pandemic, to highlight some similarities and differences. Moreover, we revisit specific events and political statements to assess how they were received by the market. This provides us with information about how expectations adjust over time and how useful option-implied information is.

Option prices have potentially much to contribute to the understanding of crises. First, similar to other financial assets, options deliver an ex-ante view on future cash flows. This view is not influenced by ex-post interpretations of events and hindsight bias. In contrast to other assets, like stocks, options add further dimensions to the study of crises. First, because options with different strike prices are traded simultaneously, they allow for the recovery of full (risk-neutral) price distributions, going beyond the expected value of discounted future cash flows. Second, because options with different times-to-maturity also trade simultaneously, market reactions referring to different time horizons are observed. Because of these further dimensions options might tell the story of a crisis quite differently from stocks.

Our paper asks three questions about the GFC and the COVID-19 pandemic. First, when was the options market able to realize the upcoming of a severe crisis? In particular, we use the risk-neutral distribution to assess when a specific crisis scenario is visible that manifests as a second mode in the left tail of the distribution. Second, what did options markets say about the magnitude of the two crises in terms of potential losses in the

[44]The Global Financial Crisis is alternatively called Great Recession in the literature. We use the term Global Financial Crisis throughout this paper.

stock market? This question is interesting because the answer tells decision makers which extreme scenarios they have to take seriously. Moreover, it is important to assess how specific events and policy measures have changed the market view on the severity of the crisis. Third, how long did the options market expect the respective crises to last? This question has two aspects. When did the markets expect to reach a post-crisis period? In how far is this post-crisis period similar to the pre-crisis period? In this paper, we shed light on these questions.

With respect to the first question, we find that options markets take time to detect the potential of a severe crisis for both the GFC and the COVID-19 pandemic. However, there is also a marked difference between the two crises, which is in line with the idea that they represent two different types of systemic shocks: The financial crisis shows different ups and downs in crisis expectations, whereas the pandemic shows a quick and rapid risk increase, followed by a quick easing. With respect to the expected magnitude of a crash scenario, both crises are astonishingly similar at their respective peaks. Other interesting findings are the market reactions to specific events. Lehman Brothers' bankruptcy is usually seen as a major signal for a potential crash. At the time of the event, however, options markets did signal high uncertainty but not a clear crash scenario. In contrast, President Trump's declaration of a national emergency in the course of the COVID-19 pandemic led to perceived risk reduction in major parts of the risk-neutral distribution but also to the emergence of a distinct crash scenario. Such results become only visible through the full risk-neutral distribution and cannot be seen from second or third risk-neutral moments alone. On the question on how long markets did expect the crisis to last, we see that a new steady state after the GFC was reached. This new regime, however, is characterized by perceived higher risks or a higher risk aversion of market participants. For the pandemic, it is still unclear whether we have reached a new steady state even at the end of June 2021, the end of our data period. Although the recovery from the pandemic was quick, there was still an ongoing trend towards a more negative skewness of the risk-neutral distribution. This ongoing trend could indicate growing risk, growing risk aversion or both. Perhaps, markets are not sure that the crisis is really over.

Our paper makes contributions to three strands of literature. The first strand of literature refers is the usage of option-implied information for the assessment and prediction of risk.

This literature started with simple applications of Black-Scholes implied volatility[45], was extended to implied betas and correlations (Buss and Vilkov, 2012; Chang et al., 2012; Kempf et al., 2015) as well as the estimation of tail risk and rare events (Ilhan et al., 2021; Bollerslev and Todorov, 2011). In our study, we do not use implied information for risk prediction but for an understanding of the ex-ante market view on the two crises. Moreover, we employ full risk-neutral densities for our analysis.

The second strand of literature refers to the analysis of systemic crises, in particular the GFC and the COVID-19 pandemic. Spatt (2020) provides a broad comparison of the two crises from a variety of different perspectives but does not use option-implied information. Nieto and Rubio (2022) compare the performance of factor portfolios during the two crises and imply expected risk premia from option prices. However, they do not look at risk-neutral distributions of the stock market. Closest to our paper are the studies by Birru and Figlewski (2012), Hanke et al. (2020) and Jackwerth (2020). Birru and Figlewski (2012) provide an analysis of risk-neutral densities in the course of the GFC. Their focus, however, is more on the relation between the options market and the stock market, whereas our focus is more on specific events. Moreover, as their sample ends in November 2008, Birru and Figlewski (2012) do not address our third question on how long the crisis was expected to last. Hanke et al. (2020) and Jackwerth (2020) use risk-neutral densities implied from option prices to analyze the COVID-19 pandemic. Hanke et al. (2020) concentrate on the comparison between different markets, whereas Jackwerth (2020) addresses some similar questions than our study. However, the focus of our study is more on the impact of specific events. Moreover, as the data periods in Hanke et al. (2020) and Jackwerth (2020) end in May 2020, these studies are unable to investigate our third research question. Another important difference is that neither study compares the COVID-19 pandemic with the GFC.

The third strand of literature refers to the analysis of policy measures during crises, in particular with respect to market reactions. There is research analyzing these issues both for the GFC (Islam and Verick, 2011) and the COVID-19 pandemic (Deng et al., 2022). What distinguishes our work from these analyses is the use of market information that goes beyond the simple price reaction of the stock market itself but includes option markets.

[45] An overview of this literature is given in Christoffersen et al. (2013).

Our study is structured as follows: Section 4.2 describes our data sources and empirical methodology. The following Section 4.3 delivers the empirical results. Its structure follows our three main research questions. A conclusion is provided in Section 4.4.

4.2 Data and Methodology

4.2.1 Data Sources and Filters

For our analyses, we use the OptionMetrics IvyDB database, which contains daily observations for all US exchange-listed options written on individual stocks and stock indexes. We obtain best bid and best ask prices, expiration dates, strike prices, implied volatilities as well as settlement information of index options written on the Standard & Poors 500 (S&P 500) index from the database. Implied volatilities are calculated by OptionMetrics' proprietary algorithm that also accounts for potential early exercise of puts. Note that S&P 500 options are European-style options. In addition to the options data, we also extract information about the underlying index from OptionsMetrics. These include daily closing prices (index levels) as well as forward prices. Forward prices are also calculated by OptionMetrics and represent the closing price of the index plus interest less projected dividends for the given time period. Lastly, we use risk-free rates for different maturities that are also provided by OptionMetrics. From this data, we calculate a risk-free rate matching the maturity of an option via interpolation. For interpolation, we use a cubic spline following Forsythe et al. (1977). Our data sample covers the periods from 01 June 2007 to 31 December 2009 and from 01 January 2020 to 30 June 2021.[46]

The options data is filtered using standard data filters (Figlewski, 2009). We require the best bid to be above \$0.5, the midpoint of best bid and best ask above \$1/8 as well as the spread between best bid and best ask to be above \$0.05. Additionally, the implied volatilities must be available and options are required to have standard settlement.[47] Further, we apply standard no-arbitrage filters, namely $max(0; S(t) \cdot e^{-d \cdot \frac{\tau}{365}} - K \cdot e^{-r \cdot \frac{\tau}{365}}) \leqslant C(t,T;K) \leqslant S(t) \cdot e^{-d \cdot \frac{\tau}{365}}$, where $C(t,T;K)$ is the price at time t of a call with maturity date T and strike price K. $S(t)$ is the spot price of the underlying, r the risk-free rate, d

[46]Note that these periods do not coincide with our definitions of crisis periods.

[47]Standard settlement means that 100 stocks are to be delivered upon exercise. In case of index options, which are usually settled with cash, one index point equals \$100 to calculate the payoff at exercise.

the dividend yield and τ the time-to-maturity in calendar days. The filters are analogously applied to put options.

4.2.2 Calculation of Risk-neutral Densities

The calculation of risk-neutral densities from option prices follows the methodology in Figlewski (2009). The starting point of this methodology are the implied volatilities of out-of-the-money (OTM) calls and puts from OptionMetrics that remain after all filters have been applied. To smooth out the jump in implied volatilities that is usually present when moving from OTM calls to OTM puts with strikes around the current spot price of the underlying, we blend the implied volatilities of these options using the formula

$$IV_{blend}(t,T;K) = w \cdot IV_{put}(t,T;K) + (1-w) \cdot IV_{call}(t,T;K), \tag{4.1}$$
$$\text{where } w = \frac{K_{high} - K}{K_{high} - K_{low}}.$$

In Equation (4.1), IV is the implied volatility at time t of an option with expiration date T and strike price K. K_{high} and K_{low} are determined such that K_{high} is the highest traded strike equal or below $S(t) + 20$ and K_{low} is the lowest traded strike equal or above $S(t) - 20$.

The implied volatilities for available strikes are smoothed using a spline function of 4th order. A dense grid of 12,000 equally spaced strike prices on the interval $[0.001,\ 3 \cdot S_t]$ is then selected. For all strikes from that grid that fall in the range of traded options, the corresponding implied volatilities are recorded and then converted back into option prices using the Black and Scholes (1973) pricing formula.[48] The risk-neutral distribution function at strike price K is then calculated as the numerical derivative of the option price with respect to the strike. For put options, this is done via the formula[49]

$$F(t,T;K_n) = e^{r \cdot \tau/365} \cdot \frac{P(t,T;K_{n+1}) - P(t,T;K_{n-1})}{K_{n+1} - K_{n-1}}, \tag{4.2}$$

[48] Note that this procedure does not assume the Black-Scholes model to hold. It just uses the Black-Scholes implied volatilities as an alternative metric that is better suited for interpolation and smoothing than the prices themselves.

[49] An analogous formula for call options is provided in Figlewski (2009). The original idea goes back to the seminal work by Breeden and Litzenberger (1978).

where $P(t, T; K_{n+1})$ represents the price of a put at time t with maturity date T and strike price K_{n+1}, which is the next available strike price above strike price K_n (K_{n-1} is analogously the next strike price below K_n). The risk-neutral density function is then calculated as the numerical derivative of the distribution function from above with respect to the strike price, using the formula

$$f(t, T; K_n) = \frac{F(t, T; K_{n+1}) - F(t, T; K_{n-1})}{K_{n+1} - K_{n-1}}. \tag{4.3}$$

With this procedure, the highest and lowest observations (strikes) get lost due to data unavailability. However, according to Figlewski (2009), the procedure delivers a satisfying shape of the risk-neutral density.

4.2.3 Calculation of Model-free Implied Moments

In our analyses to come, we augment information about the whole risk-neutral density with information about risk-neutral volatility and skewness. The calculation of model-free implied (i.e., risk-neutral) variance and skewness follows the methodology in Bakshi et al. (2003). To be consistent, the calculations use the same set of options as the estimation of the whole risk-neutral densities. The model-free risk-neutral variance[50] is obtained via the formula

$$\begin{aligned} V(t, T) = & \int_{S(t)}^{\infty} \frac{2(1 - ln[\frac{K}{S(t)}])}{K^2} C(t, T; K) dK \\ & + \int_{0}^{S(t)} \frac{2(1 + ln[\frac{S(t)}{K}])}{K^2} P(t, T; K) dK, \end{aligned} \tag{4.4}$$

and the model-free risk-neutral skewness is calculated as

$$\begin{aligned} W(t, T) = & \int_{S(t)}^{\infty} \frac{6ln[\frac{K}{S(t)}] - 3(ln[\frac{K}{S(t)}])^2}{K^2} C(t, T; K) dK \\ & - \int_{0}^{S(t)} \frac{6ln[\frac{S(t)}{K}] + 3(ln[\frac{S(t)}{K}])^2}{K^2} P(t, T; K) dK. \end{aligned} \tag{4.5}$$

[50]When we talk about model-free risk-neutral volatility, we just mean the square root of the risk-neutral variance.

The integrals in the above equations are calculated over the same discrete set of strike prices that we used for the estimation of implied densities, as explained in the previous subsection. Thus, implied moments are essentially calculated from our implied density functions. As skewness is usually normalized, we do the same and obtain normalized skewness as

$$W(t,T)_{norm} = \frac{W(t,T)}{V(t,T)^{3/2}}. \tag{4.6}$$

4.3 Empirical Results

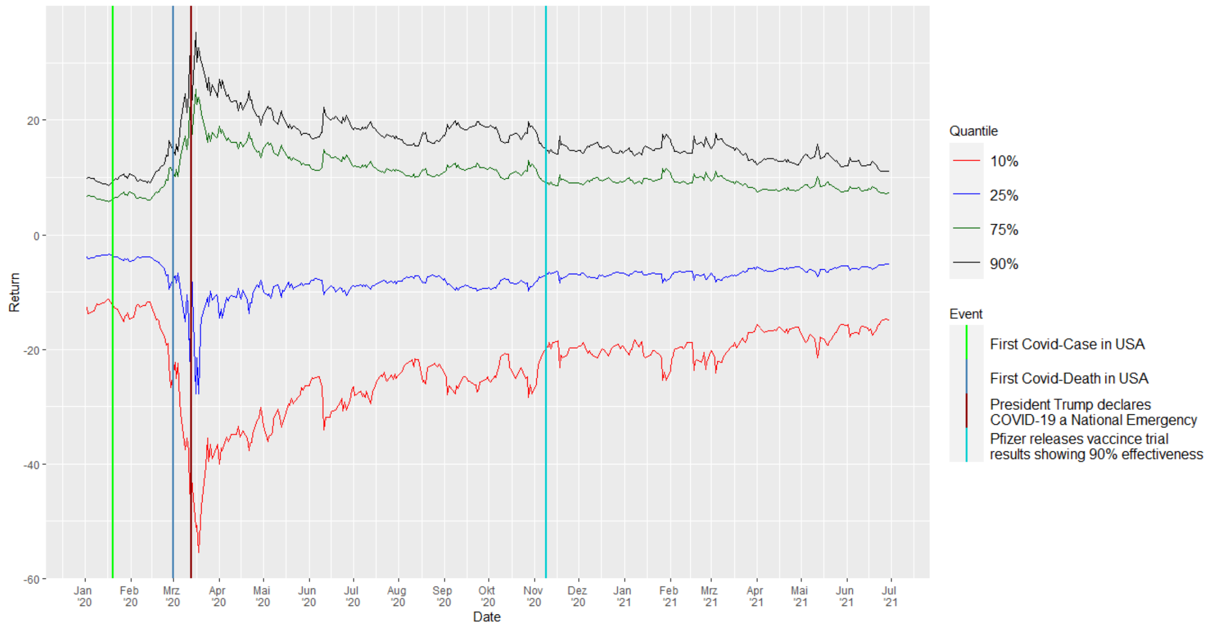
4.3.1 When Did Markets Expect an Economic Impact of the Crises?

This paper tells the story of two crises from the perspective of financial markets, i.e., it uses information contained in asset prices. The S&P 500 and the VIX are two important marked-based indicators in this respect. However, they just deliver two numbers at a given point in time. To get a more comprehensive view of market expectations, we complement this information by whole risk-neutral densities (RNDs) of S&P 500 returns. This approach adds two dimensions: First, by looking at different strike prices, we can infer a variety of quantiles of the RND. Second, as options with different times-to-maturity are available at the same point in time, we can infer market expectations for different time horizons.

We start our analysis with the COVID-19 crisis. Figure 4.1 shows the time series of four different quantiles (10%, 25%, 75%, 90%) of the RND from 01 January 2020 to 30 June 2021, where the options' time-to-maturity is held fixed at six months. In addition, potentially important events of the COVID-19 crisis are indicated with vertical lines. These events are the first documented COVID-19 case in the US, the first death in the US due to COVID-19, President Trump's declaration of a national emergency, and Pfizer's release of results about successful vaccine trials.

As Figure 4.1 shows, the inter-quartile range of the RND is relatively narrow at the beginning of 2020. The 25% and 75% quantiles are at -3.86% and 6.58%, respectively, on 01 January. The more extreme quantiles, 10% and 90%, take values of -12.72% and 9.38%. The quantiles remain relatively stable at these levels until mid-February, which is consistent with the results of Hanke et al. (2020). Only a small reaction can be seen

Figure 4.1: Time Series of Risk-Neutral Quantiles From 01.01.2020 to 30.06.2021 With Important Events During the Crisis



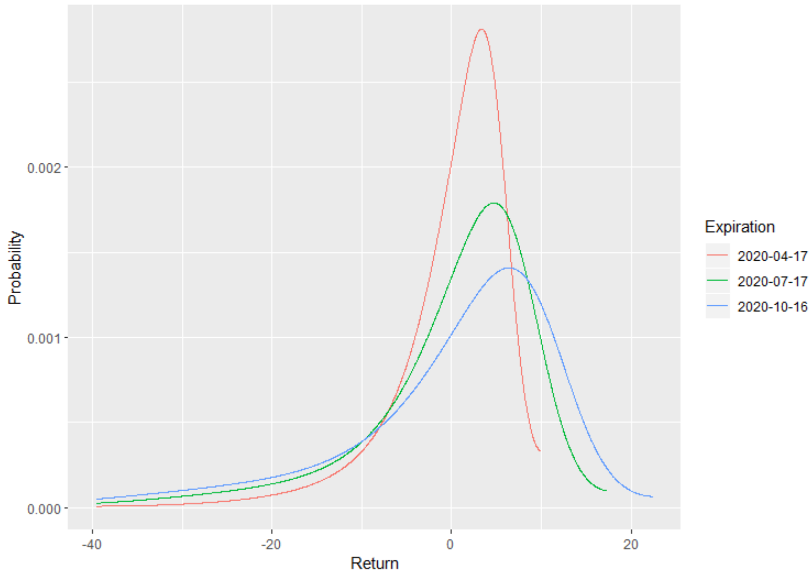
Note: This graph charts the time series of the 10%-, 25%-, 75%- and 90% quantiles of the six-months RND at the given point in time from 01 January 2020 to 30 June 2021. The expiration dates of the respective options are chosen to be closest to a time-to-maturity of six months.

after the appearance of the first confirmed COVID-19 case in the US. However, this slight reaction, which is most notable for the 10% quantile (red line), is actually not permanent and the quantile reverses back to the pre-crisis level until mid-February.

Looking at full RNDs supports this view. Figure 4.2 shows such full RNDs for time horizons of three, six and nine months, respectively, at the day of the first confirmed COVID-19 case in the US. The RNDs show no signs of a crash scenario, i.e. no bimodal distribution with a second mode in the region of extreme losses. All three distributions are negatively skewed, however, as is typical even in non-crisis periods because risk-neutral distributions also reflect risk aversion (Bakshi et al., 2003). From mid-February on, the quantiles of the left and right tail diverge quickly until the peak of the crisis (in terms of extremity of quantiles) on 16 March 2020. But even when the first COVID-19-related death in the US occurs on 01 March 2020, the RNDs do not show signs of a specific crisis scenario, i.e. a second mode, as can be seen in Figure 4.3.

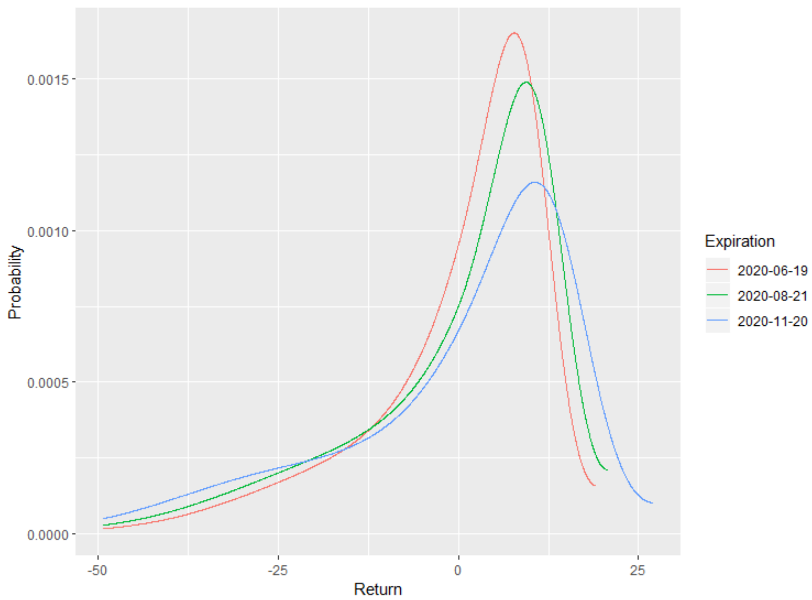
The left tails of all three RNDs stretch out, as compared to Figure 4.2, but investors do not price a distinct crash scenario. Only the RND over the longest horizon (blue line)

Figure 4.2: Risk-Neutral Densities on 21.01.2020 (First COVID-19 Case in US) With Times Horizons of Around Three, Six, and Nine Months



Note: This graph shows the RNDs on 21 January 2020 with expiration dates on 17 April 2020, 17 July 2020 and 16 October 2020.

Figure 4.3: Risk-Neutral Densities on 02.03.2020 (First COVID-19 Death in US) With Times Horizons of Around Three, Six, and Nine Months

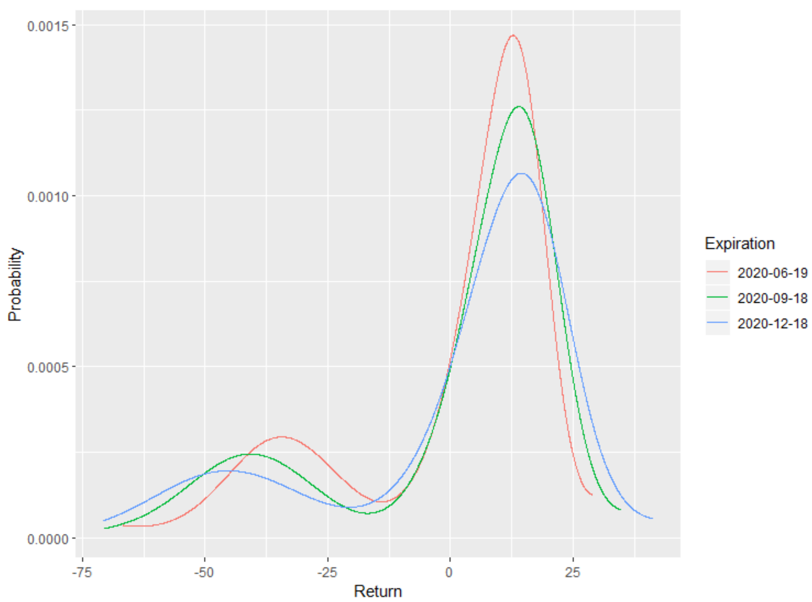


Note: This graph shows the RNDs on 02 March 2020 with expiration dates on 19 June 2020, 21 August 2020 and 20 November 2020.

shows some indications of increased probabilities in the left tail that could develop into a second mode. However, the risk-neutral probabilities are still quite low.

On 13 March 2020, President Trump declared COVID-19 a national emergency (Trump, 2020). The market reactions to this event are particularly interesting. The 25% quantile in Figure 4.1 shows a sharp increase (from -22% to -6%). A strong movement towards the center of the distribution is also notable for the right-tail quantiles but only barely visible in the 10% quantile. A possible explanation is that investors considered Trump's declaration informative in two respects: First, it reduced uncertainty because the government now seemed to take the COVID-19 pandemic more seriously. This is in line with a largely reduced inter-quartile range. Second, Trump's declaration does not seem to have mitigated the chance of an extremely negative scenario (i.e., the 10% quantile), as the disease was already spreading across the country. If the economic impact was going to be severe, the declaration of a national emergency would not change that significantly. To the contrary, if even President Trump admits serious problems, the declaration may be seen as a confirmation that a crash scenario was a realistic eventuality. The full RNDs, as shown in Figure 4.4, give additional insights into the expectations on the day the proclamation was made.

Figure 4.4: Risk-Neutral Densities on 13.03.2020 (COVID-19 National Emergency) With Times Horizons of Around Three, Six, and Nine Months

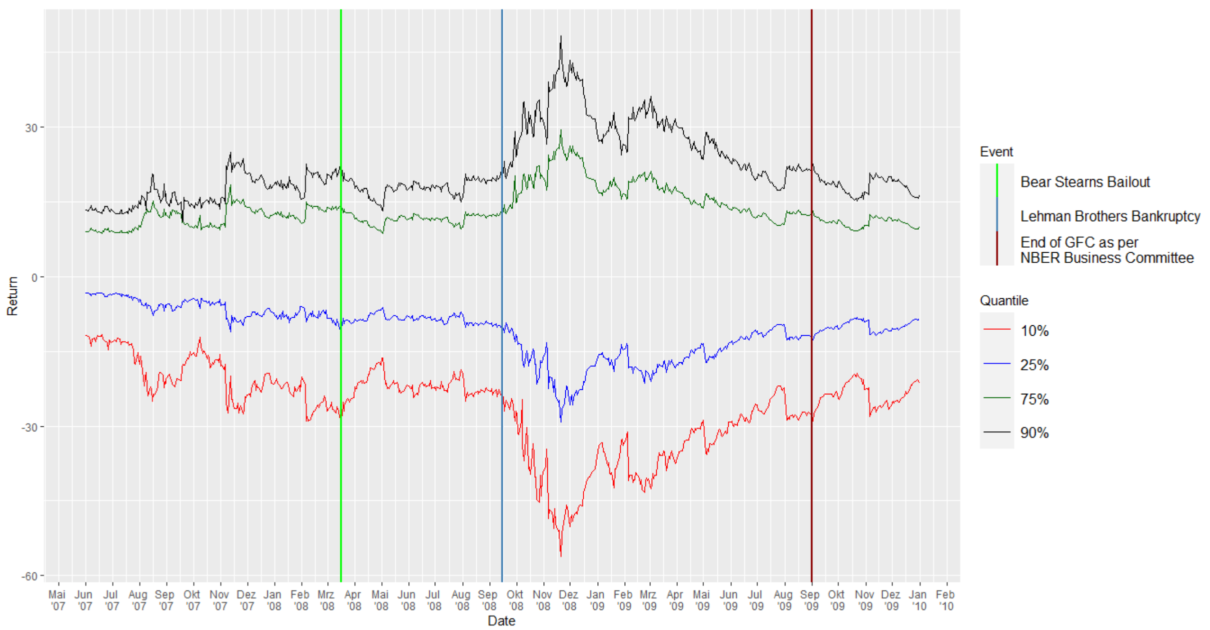


Note: This graph shows the RNDs on 13 March 2020 with expiration dates on 19 June 2020, 18 September 2020 and 18 December 2020.

Bimodal shapes of the RNDs are clearly notable for all three horizons. Hence, the RNDs are consistent with expectations expressed by two distinct scenarios: First, the government would be able to temper the crisis and the index would stabilize (indicated by the right mode). Second, the proclamation indicates a truly severe crisis that is not to stop any more (as indicated by the left mode). The expectation about the first scenario changed quickly over the weekend from 14/15 March 2020. Actually, the crisis reaches its peak on 16 March 2020, with the VIX reaching an all-time high at 82.69 and RNDs over all horizons showing severe crash scenarios. We will look at these issues in more detail in the next subsection.

The global financial crisis (GFC) has similarities but also important differences to the COVID-19 crisis. Figure 4.5 shows the time series of four different quantiles (10%, 25%, 75%, 90%) of the RND for a fixed time horizon of six months from 01 June 2007 to 31 December 2009.[51] Again, important events are marked via vertical lines: the bailout of Bear Stearns, the collapse of Lehman Brothers and the official end of the crisis, as announced by the NBER Business Committee.

Figure 4.5: Time Series of Risk-Neutral Quantiles From 01.06.2007 to 31.12.2009 With Important Events During the Crisis



Note: This graph charts the time-series of the 10%-, 25%-, 75%- and 90% quantiles of the six-months RND at the given point in time from 01 June 2007 to 31 December 2009. The expiration dates of the respective options are chosen to be closest to a time-to-maturity of six months.

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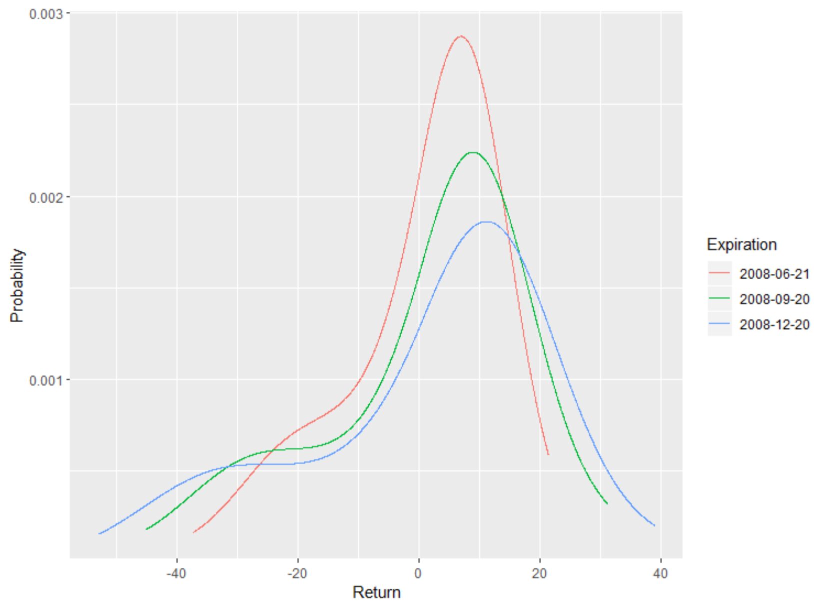
[51] Even though the NBER Business Cycle Committee defines 01 September 2009 as the end of the crisis, we show the further development of quantiles the see how investors' expectations evolve after the announcement that the crisis is over.

It is clearly evident that it took much longer than during the COVID-19 crisis until investors started to price in a sizable crash scenario. At the beginning of the crisis, delinquencies in the subprime market increase and it becomes clear that Bear Stearns has serious problems (Sean and Margraf, 2012). However, the quantiles show no signs of a crash scenario until February 2008 when foreclosures had increased 60% year-over-year (Rooney, 2008). The 10% quantile then moves downwards until the problems of Bear Stearns are of such severity that it requires a bailout and is sold to J.P. Morgan Chase & Co. on 17 March 2008. Although the VIX reached its highest level since the beginning of the GFC on that day, the level was only 32.24 points.[52] However, the path up to this day was not smooth but the VIX heavily fluctuated which indicates the high uncertainty about the risk inherent in the financial system. Such market expectations can be explained by the lack of opacity regarding the overvaluation of subprime holdings. Such lack of transparency makes it very difficult to assess the current situation and the risk in the financial sector (Spatt, 2020).

Figure 4.6: Risk-Neutral Densities on 17.03.2008 (Bear Stearns Bailout) With Times Horizons of Around Three, Six, and Nine Months

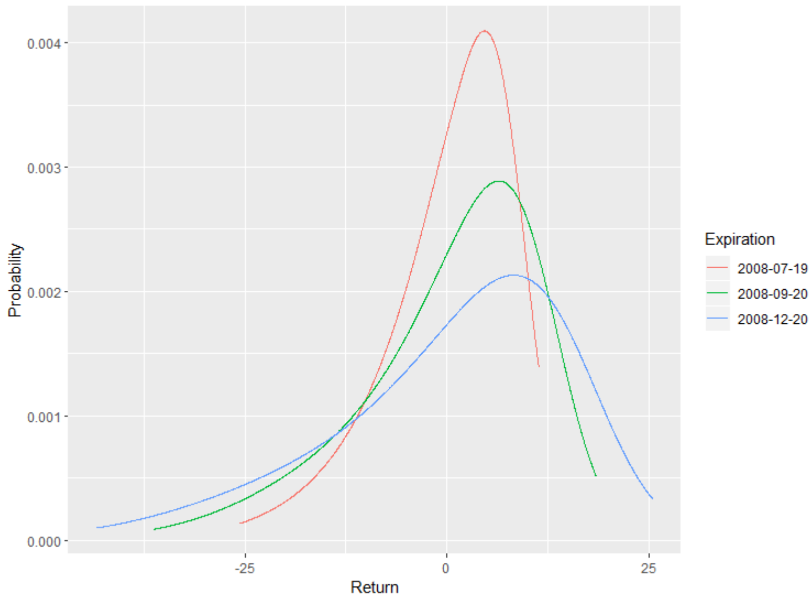


Note: This graph shows the RNDs on 17 March 2008 with expiration dates on 21 June 2008, 20 September 2008 and 20 December 2008.

[52]Although it was not introduced at the time, the VIX would have reached levels of 45 during the periods of high volatility in autumn 1998 in which BankAmerica Corp. reported a 76% fall in earnings (BIS, Committee on the Global Financial System, 1999).

Although the VIX level of 32.24 does not necessarily indicate a crisis, the risk-neutral densities show clearly increased probabilities in the left tail. Figure 4.6 shows the RNDs on the day of the Bear Stearns bailout for time horizons of three, six and nine months, respectively. The shapes of the RNDs indicate expectations of considerable crash risk. However, the news that Bear Stearns gets sold to J.P. Morgan Chase & Co. is interpreted positively by the market. All quantiles in Figure 4.5 show signs of easing after that event, as they decrease in absolute terms. Especially the 10% quantile increased from -27.97% on the day of the Bear Stearns bailout to -16.34% on 02 May 2008. On 02 May 2008, the pricing of a crash scenario vanishes completely in the RNDs over the short, medium and long horizon as shown in Figure 4.7.

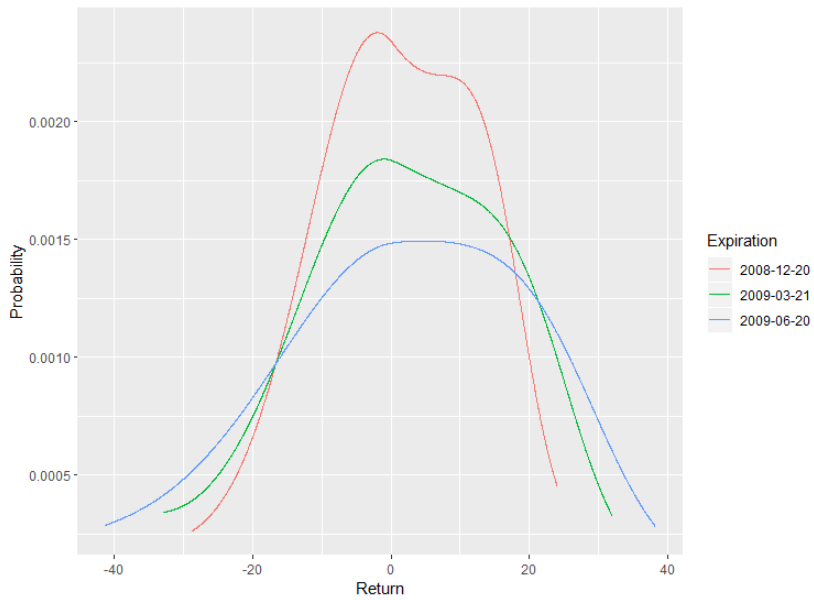
Figure 4.7: Risk-Neutral Densities on 02.05.2008 With Times Horizons of Around Three, Six, and Nine Months



Note: This graph shows the RNDs on 02 May 2008 with expiration dates on 19 July 2008, 20 September 2008 and 20 December 2008.

The RNDs on 02 May 2008 are visibly negatively skewed and the left tails stretched out. Compared to the RNDs on 17 March 2008, however, investors do not seem to expect a severe crash scenario any more. This is a considerable shift in expectations about the economic impact of the crisis in roughly two months. The expectations change significantly again on the day of the Lehman Brothers bankruptcy which can be seen as the starting point of the “deep crisis”, as shown in Figure 4.5. Interestingly, investors seem to have been unaware of the serious cascading effects of the Lehman Brothers bankruptcy. Rather, they do not know how to evaluate this event. Figure 4.8 shows the RNDs on the day Lehman Brothers declares bankruptcy.

Figure 4.8: Risk-Neutral Densities on 15.09.2008 (Lehman Brothers Bankruptcy) With Time Horizons of Around Three, Six, and Nine Months

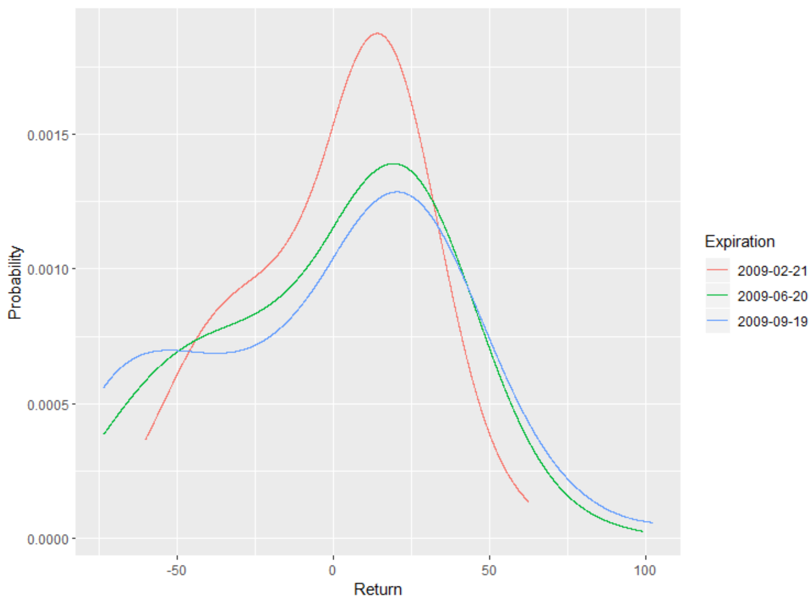


Note: This graph shows the RNDs on 15 September 2008 with expiration dates on 20 December 2008, 21 March 2009 and 20 June 2009.

As the RNDs show, investors do not expect a severe crisis even though Lehman Brothers went bankrupt. Rather, they could not classify the event and could not easily assess its severity, as indicated by the comparatively wide, plateau-like distributions. Only a slightly negative return is viewed as most likely under the risk-neutral measure. Although the Lehman bankruptcy is often seen as a massive negative signal that led to massive negative consequences, it is important to confront this interpretation with the ex-ante perspective of the options markets. At the time of the event, there were actually different views on the policy the US government should follow with respect to the crisis. One view was that the bankruptcy of a large player would further destabilize the financial system. This is the view we could all agree with in hindsight. Another view, however, was that denying to bail out Lehman Brothers would signal that excessive risk taking is not necessarily backed by the government even for a “too big to fail” institution. This signal should have a disciplinary effect on financial institutions and stabilize the financial system. As the RNDs show, the options market was not so clear on its assessments of these two views at the day of Lehman Brothers’ bankruptcy.

From the day of Lehman Brothers' bankruptcy on, expectations changed rapidly towards a crisis scenario as shown in Figure 4.5. The left tail quantiles increase considerably more quickly in absolute terms than the right tail quantiles, leading to a further stretched out left tail that reaches far into more negative expected return outcomes. This process continues until the pricing of a crash scenario at the beginning of November 2008, shortly before the peak of the crisis (from an options perspective) on 20 November 2008. On this day, the RNDs show the most extreme quantiles analogously to 16 March 2020 during the COVID-19 crisis. Moreover, as shown in Figure 4.9, there is clearly a significant crash scenario, at least over the nine-months horizon.

Figure 4.9: Risk-Neutral Densities on 20.11.2008 With Times Horizons of Around Three, Six, and Nine Months



Note: This graph shows the RNDs on 20 November 2008 with expiration dates on 21 February 2009, 20 June 2009 and 19 September 2009.

As 20 November 2008 was the peak of the GFC from an options perspective, the RNDs on that day show the worst crisis expectations throughout the whole GFC. After this day, all market-based measures indicate signs of easing except for the S&P 500, which reaches its low point during the GFC on 09 March 2009. On this day, expectations have become rather optimistic, the risk-neutral probability of a market crash is much lower than on 20 November 2008.

Overall, both crises have in common that despite early signs of a crisis it takes time until investors start to change their respective expectations and price considerable crash scenarios. In the case of COVID-19, this finding could be due to the fact that initially only sectors with a high exposure to the Chinese economy are affected, which make up a small proportion of the index constituents. Other sectors are affected much later (Ramelli and Wagner, 2020). In case of the GFC, the finding could be explained by the lack of opacity regarding subprime holdings of financial institutions (Spatt, 2020). This opacity made it almost impossible to evaluate which financial institutions were affected by how much as the delinquencies in the subprime markets skyrocketed.

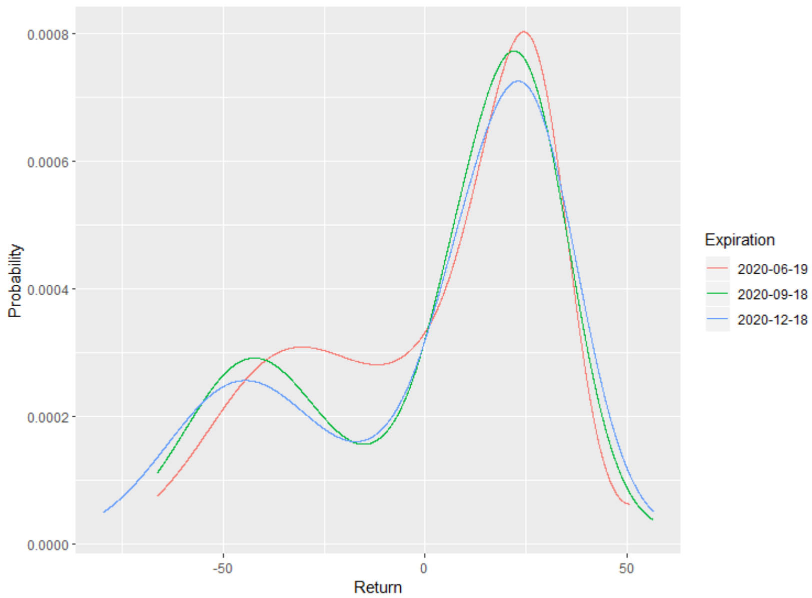
The main difference between the COVID-19 crisis and the GFC is the speed with which the crises unfolded in terms of economic impact and the fluctuation of expectations. Two months after the beginning of the COVID-19 crisis, markets started to recognize its economic impact. Only two months later, the crisis reaches its peak before easing again. In case of the GFC, the first signs of crisis expectations are visible in February 2008 and a clearly notable pricing of a crash scenario is shown on the day of the Bear Stearns' bailout on 17 March 2008, which is nine months later. However, the expectation of a crash scenario decreases again until the bankruptcy of Lehman Brothers, which is additional six months later. Even from this day on, it takes additional six months for the crisis to reach its peak from an options perspective. Hence, not only does it take much longer during the GFC until investors price significant crash scenarios but the expectations of such scenarios are fluctuating heavily. The large volatility in expectations throughout the crisis can also be explained by the lack of opacity regarding subprime holdings of financial institutions, as this volatility is an indication of the uncertainty about the risk in the financial system.

4.3.2 How Bad Did Markets Expect the Crises to Become?

As discussed in the previous subsection, the options market takes roughly two months from first signs of the COVID-19 crisis until a considerable crash scenario was priced in options. While the first case of COVID-19 in the USA is confirmed on 21 January 2020, the COVID-19 crisis reaches its peak on 16 March 2020 from an options perspective. On this day, the VIX level is 82.69, which is an increase of 547% since the beginning of the year. Shortly after (on 23 March 2020) the crisis reaches its peak on the equities market with an index level of the S&P 500 of 2237.40. This index level translates into a cumulative return of -31% since the beginning of the year. From mid-February 2020 on, the left tail of the RND reacts more strongly than the right tail, as the 10% and 25% quantiles fall from -11.64% and -3.82% to -51.10% and -27.82%, respectively, while the

75% and 90% quantiles only rise from 6.06% to 25.46% and from 9.06% to and 35.39%. These asymmetric reactions indicates a higher skewness, as the left tail gets stretched out further than the right tail. To shed more light on the expectations regarding the potential economic impact of COVID-19, Figure 4.10 shows the RNDs on the peak of the crisis on 16 March 2020 for time horizons of three, six and nine months.

Figure 4.10: Risk-Neutral Densities on 16.03.2020 With Times Horizons of Around Three, Six, and Nine Months



Note: This graph shows the RNDs on 16 March 2020 with expiration dates on 19 June 2020, 18 September 2020 and 18 December 2020.

The pricing of a crash scenario is clearly notable via the bimodal shapes of the RNDs for all three horizons. The market prices a crash scenario of -30% (mode in the left tail) over the next three months, -42% over the next six months and even 45% over the next nine months. Although the asymmetric reactions to crises suggest a more negative skewness of the RNDs, the opposite is true because the left tails not only get stretched out but also get more weight. This leads to overall more symmetric distributions with a less negative skewness than before. As discussed in the previous subsection, expectations regarding a crash scenario ease quite quickly and the left tails of the RNDs shrink again.

As discussed before, expectations regarding a crash scenario during the GFC change significantly throughout the crisis. The first pricing of a crash scenario becomes visible in the RNDs on the day of the Bear Stearns bailout on 17 March 2008, as shown in Figure 4.6. Although the RNDs are formally not bimodal, the pricing of a crash scenario is clearly notable. Over the three-months horizon, investors price a crash scenario with an expected return of around -20%. The expectation regarding a crash scenario over the following six months was around -25% while over the nine-months horizon a crash scenario of around -30% is priced. While the RNDs remain visibly negatively skewed at the beginning of March 2008, indicating high risk-aversion or high uncertainty in the physical distribution (or both), the normal scenario is not distinguishable from a crash scenario any more, as shown in Figure 4.7. The bankruptcy of Lehman Brothers is particularly interesting, as options investors do not seem to be able to classify this event as either good or bad. Over the short and middle horizon, a slightly negative return of the S&P 500 of around -2% is viewed most likely under the risk-neutral measure. However, the high uncertainty is indicated by the wide plateaus of the distributions which also reach into the positive return region of up to +13%. This could be due to the fact that bailouts of financial institutions with taxpayers' money were hugely unpopular at the time of the bailout of Bear Stearns and Fannie Mae and Freddie Mac were bailed out shortly before the bankruptcy of Lehman Brothers (Kessler, 2018).

The following two months made clear that the Lehman bankruptcy would not lead to a recovery of financial markets. As shown in Figure 4.5, it marks the starting point of a deep financial crisis which reaches its peak on 20 November 2008 from an options perspective. On that day, the VIX reaches a level of 80.86 and the 10% (25%) quantiles fall to -56.22% (-29.12%) from -24.19% (-10.74%) on the day of the Lehman Brothers' bankruptcy. In roughly two months, the 10% quantile more than doubles in absolute terms and the 25% quantile almost triples, as shown in Figure 4.5. All RNDs show the pricing of notable crash scenarios. The crash scenario is most pronounced over the long horizon, as shown in Figure 4.9. Over the following nine months, investors expect a crash scenario of around -50%. Over the short and middle horizons, the expected returns of the crash scenarios are higher and harder to distinguish from the normal scenario as the distributions are not strictly bimodal.

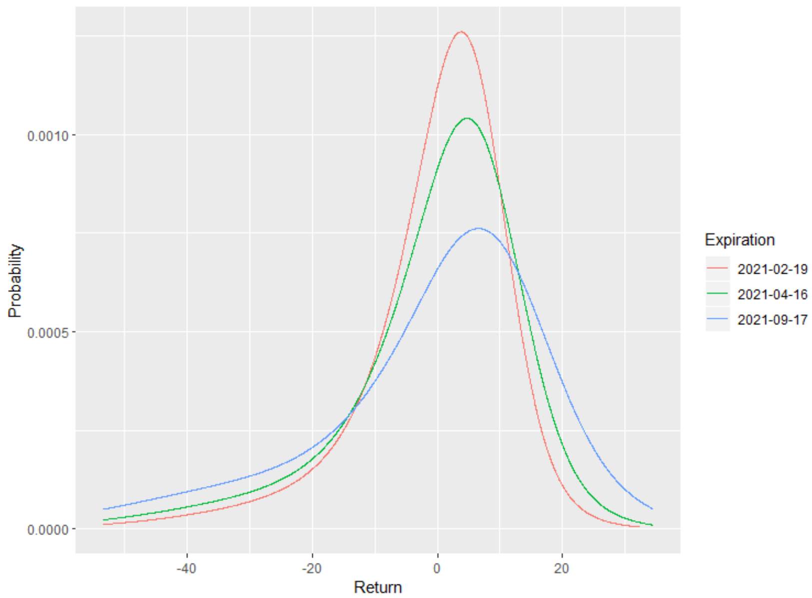
Overall, during the GFC as well as the COVID-19 crisis, investors expect similar crash scenarios with respect to their magnitude. While the expectations during the GFC were a bit more pessimistic with a 10% quantile of -56.22% and a priced crash scenario over the nine-months horizon of around -50%, the differences are minor. The 10% quantile at the height of the COVID-19 crisis was at -51.10% and the priced crash scenario over the nine-months horizon was -45%.

The main difference, again, is the fluctuation of expectations during the GFC. During the COVID-19 pandemic, once the options market starts to recognize the economic impact of the health crisis, a crash scenario is visible at the beginning of March 2020 and reaches its peak on 16 March 2020. After this day, the markets calm down without pricing a distinct crash scenario ever again. During the GFC, however, the first pricing of a crash scenario happens on the day of the Bear Stearns bailout. At that time, the expected returns of a crash scenario are between -20% and -30% over the following three to nine months. Thereafter, the options market calms down again, making it impossible to distinguish between a crash- and a normal scenario in the RNDs. Even on the day of the Lehman Brothers bankrupcy, investors do not expect a severe crash. However, the uncertainty was quite high as investors apparently could not classify the event and its implications on the financial industry and the economy as a whole. Only two months later, the options market prices severe crash scenarios for all analyzed horizons with the aforementioned expected return of around -50% over the next nine months.

4.3.3 How Long Did Markets Expect the Crises to Last?

The question how long investors expected the crisis to last is particularly interesting for the COVID-19 crisis, as there is no official end date. As discussed in the previous subsection, after the peak of the crisis on 16 March 2020, the markets show signs of easing. While the S&P 500 continues to fall after the peak of the crisis according to options markets, even the equities market reaches its peak (low point) only seven days later on 23 March 2020. After this day, both the VIX and the S&P 500 recover quickly but also differently. The S&P 500 reaches its pre-crisis level of 3257.85 already on 21 July 2020, so a little later than eight months after the beginning of the crisis. And the index continues to rise even after this day. The options market, however, does not recover as quickly to pre-crisis levels, indicating that investors are still cautious. This is in line with local lockdowns still occurring and the virus still spreading across the country. On 09 November 2020, Pfizer and BioNTech release the trial results of their vaccine candidate against COVID-19, showing a 90% effectiveness (Pfizer and BioNTech, 2020). These results are a major step towards solving the health crisis. However, as shown in Figure 4.1, the news do not cause a major reaction on the options market. All quantiles are still heightened compared to pre-crisis levels and especially the left tail quantiles are away from pre-crisis levels with the 10% quantile at -19.79% (pre-crisis: -12.72%) and the 25% quantile at -6.94% (pre-crisis: -3.87%). The right-tail quantiles are at 9.03% (pre-crisis: 6.58%) for the 75% quantile and at 14.91% (pre-crisis: 9.83%) for the 90% quantile. The whole distribution is shown in Figure 4.11.

Figure 4.11: Risk-Neutral Densities on 09.11.2020 (Pfizer Vaccine Trial Results) With Times Horizons of Around Three, Six, and Nine Months

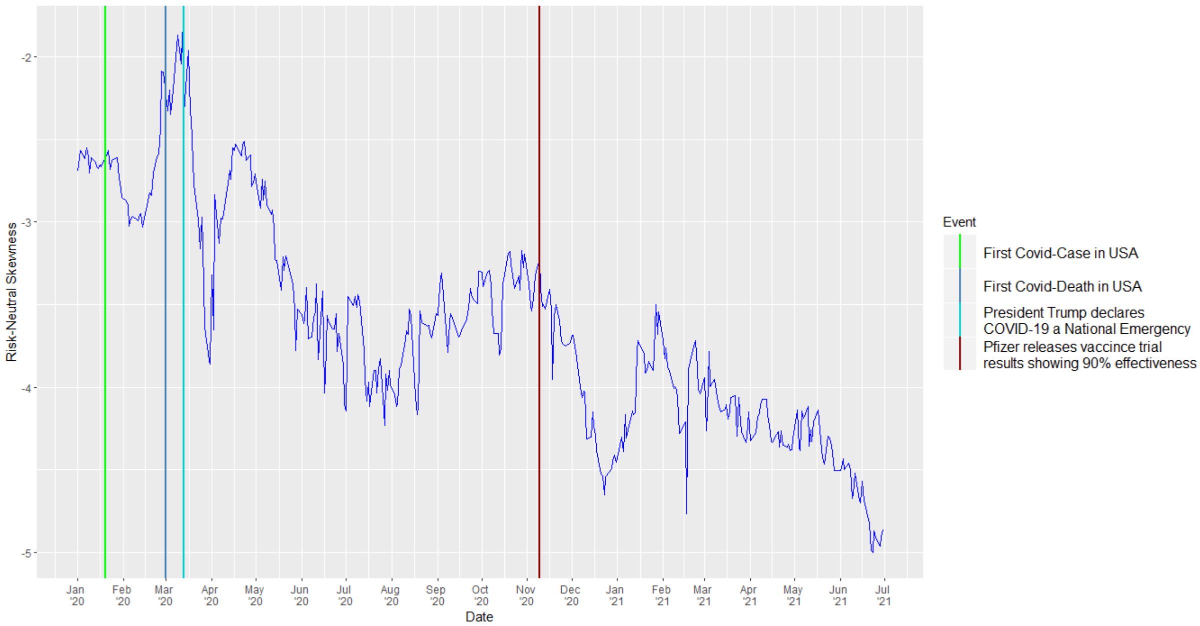


Note: This graph shows the RNDs on 09 November 2020 with expiration dates on 19 February 2021, 16 April 2021 and 17 September 2021.

All RNDs look visibly more similar to non-crisis RNDs than crisis RNDs (Figure 4.10). No signs of priced crash scenarios are visible any more. However, compared to the beginning of the crisis (Figure 4.2), the left tail is more stretched out. This observation indicates a still heightened risk-aversion or increased risk in the physical distribution (or both). A metric that indicates risk-aversion is the risk-neutral skewness (Bakshi et al., 2003). Figure 4.12 shows the time series of the risk-neutral skewness, where the time horizon is held fixed at six months.

The graph shows a clear negative trend throughout the crisis which continues until the end of the sample on 30 June 2021. Even though the equities market seems to have recovered from the COVID-19 shock and continues to rise above pre-crisis levels, investors still remain cautious. The falling risk-neutral skewness indicates growing uncertainty in the markets which confirms the impression of increasing risk-aversion or heightening downside

Figure 4.12: Time Series of Risk-Neutral Skewness From 01.01.2020 to 30.06.2021 With Important Events During the Crisis

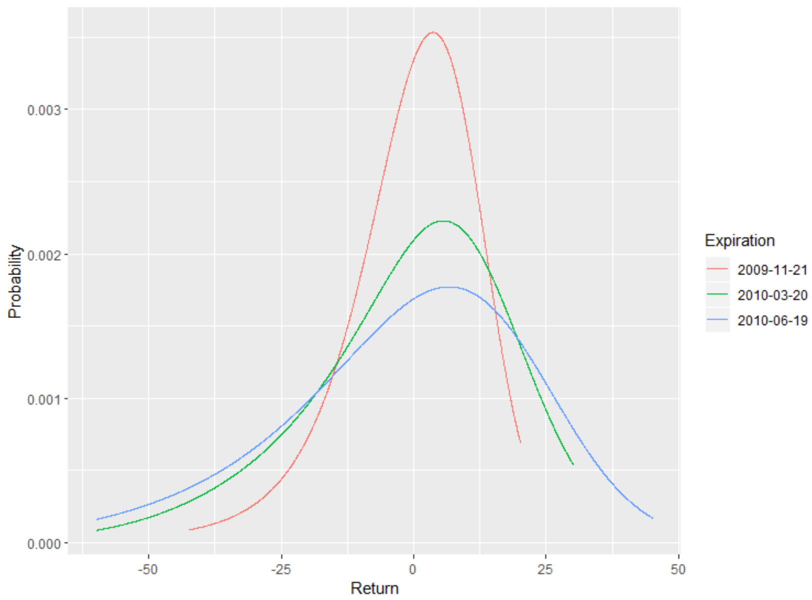


Note: This graph charts the time-series of the risk-neutral skewness of the six-months RND at the given point in time from 01 January 2020 to 30 June 2021. The expiration date of the respective options are chosen to be closest to a time-to-maturity of six months.

risk in the physical distribution (or both). This observation could be due to the fact that the virus is still spreading across the country and the health crisis is not over yet, even though the equities market recovered quickly from the initial shock. It appears that the longer the crisis continues, the more uncertainty grows. However, because the sample period ends in June 2021, it remains to investigate in future research whether this trend reverses at a future point in time or if the markets have switched to a new stationary regime with higher risk-aversion.

The GFC, contrary to the COVID-19 crisis, has an officially defined end. The National Bureau of Economic Research (NBER) defines the end of the GFC as 01 September 2009 (Nieto and Rubio, 2022). On this day, the S&P 500 has not reached its pre-crisis level of 1536.34, as it closes at 998.04. Hence, the equities market still have not fully recovered from the shock of the crisis. The official end of the GFC is marked with the vertical dark blue line in Figure 4.5. The quantiles, especially in the left tail, are still below pre-crisis levels, similar to the COVID-19 crisis. The 10% quantile is at -28.44% (pre-crisis: -11.78%) while the 25% quantile is at -12.62% (pre-crisis: -3.27%). The right-tail quantiles are also still heightened but not as much as the left-tail quantiles (also similar to the COVID-19 crisis). The 75% quantile is at 13.06% (pre-crisis: 9.08%) while the 90% quantile is at 22.66% (pre-crisis: 13.36%). However, the RNDs show no pricing of a crash scenario any more, as shown in Figure 4.13.

Figure 4.13: Risk-Neutral Densities on 01.09.2009 (Official End of GFC) With Times Horizons of Around Three, Six, and Nine Months

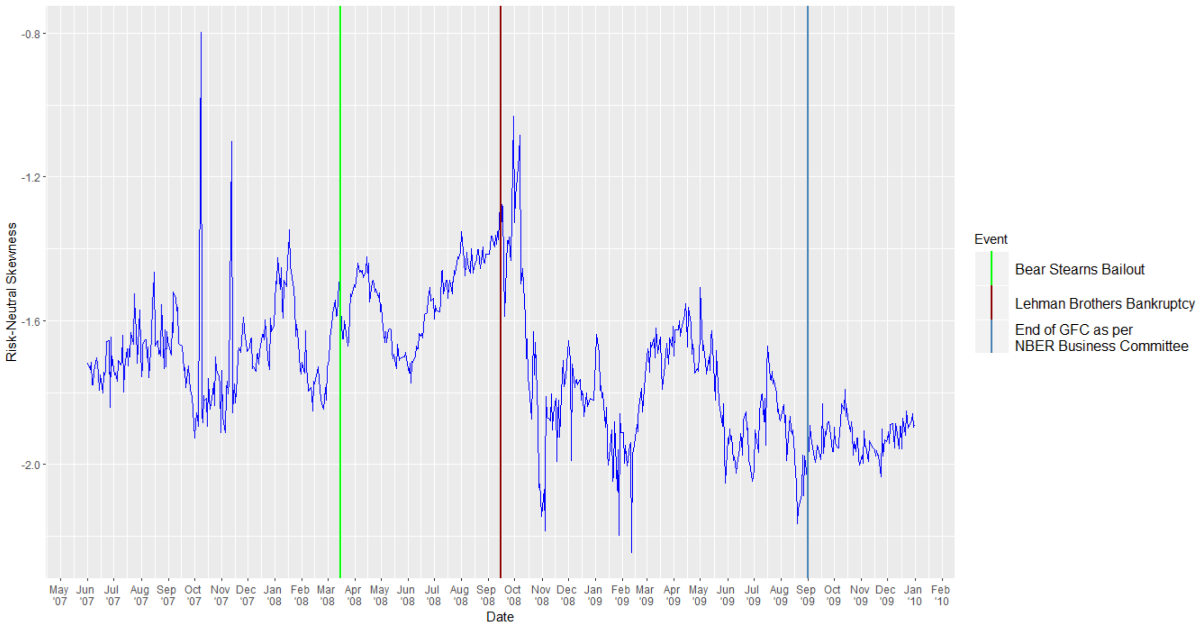


Note: This graph shows the RNDs on 01 September 2009 with expiration dates on 21 November 2009, 20 March 2010 and 19 June 2010.

The RNDs have still stretched out left tails which indicates a still heightened risk-aversion or an increased risk in the physical distribution (or both). This is similar to the COVID-19 crisis, although the left tail is stretched out even further than during COVID-19.

Particularly interesting is the time series of risk-neutral skewness. As shown in Figure 4.14, the risk-neutral skewness increases (becomes less negative) significantly during the height of the crisis which is due to increased weight of the left tail, making the whole distribution more symmetric. After the peak of the crisis, the risk-neutral skewness falls below -2. Although it recovers (becomes less negative) slightly, it appears that the markets have entered a new regime with more negatively skewed RNDs. This could be due to the fact that the crisis has reminded investors of the opacity of the financial industry, leading heightened risk-aversion or recognition of the true risks in the physical distribution.

Figure 4.14: Time Series of Risk-Neutral Skewness From 01.06.2007 to 31.12.2009 With Important Events During the Crisis



Note: This graph charts the time-series of the risk-neutral skewness of the six-months RND at the given point in time from 01 June 2007 to 31 December 2009. The expiration date of the respective options are chosen to be closest to a time-to-maturity of six months.

Overall, although the COVID-19 crisis has no officially defined end date yet, both crises have in common that investors seem to be more cautious after the crisis than in the pre-crisis period. This is indicated by the higher (i.e., more negative) risk-neutral skewness and the stretched out left tails of the RNDs. Although the RNDs at the end of the GFC look visibly more symmetrical than the RNDs on the day of the vaccine trial result disclosure by Pfizer/BioNTech, the RNDs on both days appear notably more similar to non-crisis RNDs than to the RNDs during the height of the respective crisis.

Interestingly, the equities market and the options market clearly stress different aspects of the COVID-19 crisis. While the equities market has long recovered from the crisis shock and even exceeded pre-crisis levels, the options market still shows signs of increased uncertainty or risk-aversion. This uncertainty continues to grow with the duration of the crisis and the risk-neutral skewness reaches its low point at the end of the sample in June 2021. At the end of the GFC, however, the equities market and the options market both are still recovering from the shock of the crisis. The equities market has not reached its pre-crisis level and the options market still indicates increased uncertainty. It even seems to have entered a new regime, as the risk-neutral skewness levels out at a lower (more negative) value than before the crisis. So, even though the crisis was officially declared to be over, both markets still show signs of the shock.

4.4 Conclusion

In this paper, we use information from options markets to retell the story of two crises, the GFC and the COVID-19 pandemic. Using options with different strike prices and times-to-maturity, we construct risk-neutral densities for different time horizons. Our results show both similarities and differences between the two crises.

Options markets initially take time to indicate that a crisis exists or could worsen. In contrast, markets react very quickly and in a differentiated manner to new events within the crisis. Of particular interest are the reactions of options markets to specific events, such as the bankruptcy of Lehman Brothers in September 2008 and President Trump's declaration of a national emergency in March 2020. On these dates, it would be too simplistic to speak of an increase or decrease in risk, as the shape of the RND also changes significantly. It turns out that RNDs can provide important information on the perception of events and decisions, which then again provide the basis for further decisions. Another very interesting aspect is the extent to which the stock market has already entered a post-crisis phase by June 2021, as the analyses still show a steady trend towards a more negative skewness of the RND.

Given these results, it would be interesting to follow the progress of the COVID-19 pandemic even further over time. Also, changes in risk neutral densities always provide the simultaneous effects of changes in expectations and risk preferences of market participants. Separating these two aspects would be another interesting task for further research.

5 Conclusion

This dissertation provides important contributions to a better understanding of the three main purposes of options: i) trading, ii) risk management, iii) generation of information. More specifically, this thesis presents new findings about the pricing and exposures of equity options as well as the information content of index options. Especially on the pricing and the information content of options, there is wide strands of literature that has established a variety of facts. Regarding the pricing of options, we know, for example, that delta-hedged option returns have a negative correlation with their underlying's historical idiosyncratic volatility (the low-volatility effect (Cao and Han, 2013)). Additionally, we know that delta-hedged option returns have a positive correlation with the difference between the underlying's historical realized volatility and the implied volatility of the option (the expensiveness effect (Goyal and Saretto, 2009)). The evidence on exposures of realized delta-hedged option returns is not as rich as on the determinants of expected option returns. Although determinants of expected delta-hedged option returns serve as an indication of what delta-hedged option portfolios should have exposure to[53], there is no study explicitly analysing the exposures of such portfolios. Lastly, because option prices contain information about the investors' conditional expected return distribution of an underlying (the risk-neutral density), they are particularly valuable for analyses of times of crisis like the GFC and the COVID-19 crisis (Bahra, 2007). As for the GFC, we know that the higher moments (i.e., skewness and kurtosis) decrease in magnitude and are more locally driven than volatility which is internationally more cointegrated (e.g., Birru and Figlewski, 2012; Gagnon et al., 2016). As for the COVID-19 crisis, we know that investors do not immediately shift their expectations regarding a potential crash scenario, that reactions in different countries vary depending on the strictness of the COVID-19 policy

[53]See, for example, Kim and Kim (2016); Ruan (2020); Zhan et al. (2022).

and that option premiums react to WHO announcements (Jackwerth, 2020; Hanke et al., 2020; Li et al., 2022).

These findings raise further questions that still need to be answered in the literature. The questions can be summarized into three research questions that this dissertation aims to answer one by one in the main chapters:

(i) How and why are the low-volatility and the expensiveness effect related to each other and if and how can investors exploit this relationship?

(ii) What are the exposures of delta-hedged option portfolios to different risks and their risk parts as well as to firm characteristics and how do exposures interact?

(iii) What do we learn from option-implied information about the expectation changes due to important events during the COVID-19 crisis and how does it compare with the GFC?

In the first study (Chapter 2), evidence to answer the first research question is provided. Hence, the potential relationship between the low-volatility effect and the expensiveness effect is analyzed, motivated by the recent developments in the financial intermediary asset pricing literature. We argue that the expensiveness holds valuable information about the market maker position while volatility is an indication for market imperfections. Both economic rationales are supported by the empirical results. Our findings shows a clear linkage between the two well-known anomalies: The low-volatility effect is only present in options with high expensiveness, and the magnitude of the expensiveness effect is positively correlated with idiosyncratic volatility. The study further shows that these findings are not driven by inefficiencies or times of crisis. However, although the returns of long-short strategies based on the conditional low-volatility effect and the conditional expensiveness effect show sizeable returns, only investors with low transaction costs can profitably trade on the two anomalies and exploit their relationship. But other investors can also benefit from the findings, as the effects cannot be hedged away and are not due to inefficiencies, so they are likely to persist over time and should therefore be taken into account.

The second study (Chapter 3) provides answers to the second main research question. It analyzes the exposures of delta-hedged option portfolios to different risks (measured as stock return moments) as well as to firm characteristics. The results show that delta-hedged option portfolios have exposure to the second, third and fourth stock return moment, the variance and skewness risk as well as to most but not all firm characteristics. The directions of the exposures to stock return moments and moment risks are consistent with investor preferences (e.g., Dittmar, 2002). As for the direction of the exposures to firm characteristics, some are consistent with the existing literature while others remain puzzling. Moreover, the exposures to firm characteristics are especially informative when stock return moments indicate low risk of the underlying. This suggests that firm characteristics hold additional information about the riskiness of the underlying and can therefore be interpreted as alternative risk measures.

The third study (Chapter 4) is concerned with the third research question. It analyzes and compares the GFC and the COVID-19 crisis using option-implied information. It shows that both crises have fundamental differences but also important similarities. Both crises have in common that it takes time until investors price in significant crash scenarios which are of similar magnitude on the peaks of both crises. However, it also shows that during the GFC investors' expectations vary widely over the course of 17 months. Even as the GFC was officially declared over, both the equities and the options market had not yet recovered from the shock. During the COVID-19 crisis, investors expectations do not vary as much and the crisis reaches its peak after only 3 months. Even though the crisis was not over, the equities market recovers after only 7 months from the shock of the crisis while the options market still shows signs of a heightened risk-aversion or increased uncertainty in the market (or both).

In summary, this dissertation provides contributions to the literature on volatility-related pricing, the exposures of delta-hedged option returns, and the option-implied information content that is particularly valuable in times of crisis. The main findings for each of the three main purposes of options can be summarized as follows: i) the low-volatility effect and the expensiveness effect are linked which is consistent with the existing literature on intermediary asset pricing, ii) only investors with low transaction costs can profitably trade on the conditional low-volatility effect and the conditional expensiveness effect, iii) the linkage of the two anomalies is not due to market inefficiencies or times of crisis which means that they are likely to remain and should therefore be considered even by investors with higher transaction costs, iv) delta-hedged option portfolios have exposure to volatility, skewness and kurtosis, variance risk, skewness risk as well as firm characteristics, v) the exposures of delta-hedged option portfolios are mainly driven by idiosyncratic risks, vi) the exposure to firm characteristics is particularly informative when stock return moments indicate low risk, vii) during the GFC and the COVID-19 crisis, it takes months until investors price crash scenarios which, at the peak of each crisis, are of similar magnitude, viii) during the GFC, investors' expectations vary widely and it takes roughly 17 months until the crisis reaches its peak while during the COVID-19 crisis, investors' expectations do not vary as much and the crisis reaches its peak after only two months, ix) during both crises, even long after the shock, the option-implied information indicate heightened risk-aversion or increased uncertainty in the market.

The findings of this dissertation benefit researchers and practitioners from the fields of asset and risk management, asset pricing as well as regulatory authorities. Ways to conduct future research based on the contributions are as follows. One way is to apply the economic explanation of market maker behaviour affecting option prices to other anomalies in the options market because market makers are crucial for the price setting (He and Krishnamurthy, 2013; He et al., 2017; Kargar, 2021). Hence, it stands to reason that other anomalies are also possibly linked through the behaviour of market makers. Additionally, another way to extent the results is to apply the analyses to options on other asset classes such as currencies or commodities. Cryptocurrencies are particularly interesting in this context. Given that volatility serves as a proxy for market imperfections and that cryptocurrencies usually exhibit very high volatilities, it may be fruitful to investigate whether the same patterns are also present in this asset class (e.g., Chi and Hao, 2021). Additionally, as different asset classes are affected by different determinants, an exposure analysis might be a fruitful path for future research. Moreover, a comparison of the GFC and the COVID-19 crisis in other countries may be interesting, as options markets' responses to COVID-19 differ in different countries, as each country has followed its own coping strategy and has also been affected differently (e.g., Hanke et al., 2020; Li et al., 2022).

Practitioners can benefit from the findings in this dissertation as it shows that the conditional effects of the low-volatility effect and the expensiveness effect are two to three times larger than the unconditional effects. Because institutional investors have low transaction costs, they may be able to profitably trade on them. But also other investors, for example with lottery-like preferences can benefit from the findings. Additionally, practitioners active in risk management can benefit from the exposure analyses of delta-hedged option portfolios. For risk managers, it is crucial to know their exposure to different risks to adjust their risk management strategies accordingly. Further, regulatory authorities and investors can benefit from the findings of the analyses of the GFC and the COVID-19 crisis because they show that market expectations change throughout the course of the two crises and how important events affect investors' expectations.

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Statement of contribution
to each paper of the cumulative dissertation

To the three papers of the cumulative dissertation, I personally contributed as follows:

1. to the paper *A New Look at the Cross-Section of Option Returns and Volatility* co-authored by Olaf Korn and David Volkmann: significant contributions to the conceptualization, empirical analysis, and writing, in total: 65%,

2. to the paper *Exposures of Delta-Hedged Option Portfolios* (single-author paper): conceptualization, empirical analysis, and writing, in total: 100%, and

3. to the paper *A Tale of Two Crises Told by Options* co-authored by Olaf Korn: significant contributions to the conceptualization, empirical analysis, and writing, in total: 80%.

Göttingen, 05.07.2023

Place, Date | Niklas Trappe

Ph.D. program in Economics

Declaration for admission to the doctoral examination

I confirm

1. that the dissertation "On the Determinants of Premiums in Financial Markets" that I submitted was produced independently without assistance from external parties, and not contrary to high scientific standards and integrity,

2. that I have adhered to the examination regulations, including upholding a high degree of scientific integrity, which includes the strict and proper use of citations so that the inclusion of other ideas in the dissertation are clearly distinguished,

3. that in the process of completing this doctoral thesis, no intermediaries were compensated to assist me neither with the admissions or preparation processes, and in this process,

   - no remuneration or equivalent compensation were provided

   - no services were engaged that may contradict the purpose of producing a doctoral thesis

4. that I have not submitted this dissertation or parts of this dissertation elsewhere.

I am aware that false claims (and the discovery of those false claims now, and in the future) with regards to the declaration for admission to the doctoral examination can lead to the invalidation or revoking of the doctoral degree.

Göttingen, 05.07.2023

Place, Date

Niklas Trappe