Option-implied risk measures and the cross-sectional variation of stock returns

by

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Περίληψη (summary in Greek)

Η παρούσα διδακτορική διατριβή εστιάζει στη μελέτη των πληροφοριών που εμπεριέχονται στην αγορά δικαιωμάτων προαίρεσης για την καλύτερη κατανόηση της αποτίμησης των μετοχικών τίτλων. Τα δικαιώματα προαίρεσης ενσωματώνουν πολύτιμες πληροφορίες για τις προσδοκίες των επενδυτών σχετικά με τις μελλοντικές αποδόσεις των υποκείμενων τίτλων τους. Αυτό πηγάζει από το γεγονός ότι οι αγορές είναι ατελείς λόγω περιορισμών όπως η ασύμμετρη πληροφόρηση και τα εμπόδια στην ανοιχτή πώληση, καθιστώντας τα δικαιώματα προαίρεσης μη-περιττά περιουσιακά στοιχεία.

Την τελευταία δεκαετία έγιναν πολλές μελέτες που υπολογίζουν ένα μέτρο από τα δικαιώματα προαίρεσης και εξετάζουν αν προβλέπει τις μελλοντικές αποδόσεις των μετοχών. Ενδεικτικά, οι Guo και Qui (2014) βρίσκουν αρνητική σχέση ανάμεσα στην τεκμαρτή μεταβλητότητα και τις μελλοντικές αποδόσεις των μετοχών και οι Stilger, Kostakis και Poon (2017) δείχνουν ότι η ουδέτερη ως προς τον κίνδυνο ασυμμετρία προβλέπει θετικά τις μελλοντικές αποδόσεις των μετοχών. Οι προαναφερθείσες μελέτες χρησιμοποιούν ένα μέτρο με βάση μια συγκεκριμένη ιδιότητα/ροπή της ουδέτερης ως προς τον κίνδυνο κατανομής των αποδόσεων των μετοχών και γι’ αυτό μπορεί να χάνουν πολύτιμες πληροφορίες. Στο 1ο κεφάλαιο προτείνουμε ένα από κοινού μέτρο σχετικό με την ουδέτερη ως προς τον κίνδυνο κατανομή. Πιο συγκεκριμένα, συνδυάζουμε την διακύμανση, την ασυμμετρία και την κύρτωση που τεκμαίρονται από τα δικαιώματα προαίρεσης σε ένα βαθμολογικό μέτρο με βάση τις προτιμήσεις των επενδυτών στις ροπές, δηλαδή μία χαμηλή βαθμολογία σημαίνει ότι η μετοχή έχει υψηλή διακύμανση, χαμηλή ασυμμετρία και υψηλή κύρτωση. Αντίθετα μία υψηλή βαθμολογία σημαίνει ότι η μετοχή έχει χαμηλή διακύμανση, υψηλή ασυμμετρία και χαμηλή κύρτωση. Ουσιαστικά, το μέτρο μας μπορεί να ερμηνευτεί ως ένα μέτρο αμυντικότητας, όπου ο ορισμός της επεκτείνεται λαμβάνοντας υπόψιν την ασυμμετρία και την κύρτωση μαζί με την διακύμανση.

Ταξινομούμε τις μετοχές σε χαρτοφυλάκια με βάση το βαθμολογικό μέτρο μας και βρίσκουμε ότι οι μετοχές με υψηλό σκορ έχουν μεγαλύτερες αποδόσεις από τις μετοχές με χαμηλό σκορ. Η στατιστικά σημαντική σχέση μεταξύ του μέτρου μας και των μελλοντικών αποδόσεων των μετοχών αντέχει σε διάφορα τεστ ανθεκτικότητας όπως διπλές ταξινομήσεις, Fama-MacBeth (1973) παλινδρομήσεις και χρησιμοποίηση δείγματος μετοχών μεγάλης κεφαλαιοποίησης. Δείχνουμε ότι αυτή η σχέση εξηγείται από την έκθεση στα σοκ της μεταβλητότητας της αγοράς και εξαρτάται από το επίπεδο της επενδυτικής ψυχολογίας. Σε περιόδους χαμηλής επενδυτικής ψυχολογίας το διαχρονικό μοντέλο αποτίμησης περιουσιακών στοιχείων (ICAPM) μας εξηγεί πλήρως αυτή τη σχέση, ενώ σε περιόδους υψηλής επενδυτικής ψυχολογίας η σχέση παραμένει στατιστικά σημαντική και αποδίδεται σε εσφαλμένη τιμολόγηση.

Η βιβλιογραφία έχει δείξει ότι ο κίνδυνος των αλμάτων τιμολογείται από τους επενδυτές στην αγορά των δικαιωμάτων προαίρεσης. Ένα μέρος των ερευνών εξετάζει την επιρροή του κινδύνου άλματος στα ασφάλιστρα κινδύνου των μετοχών και της διακύμανσης, παρέχοντας ισχυρές ενδείξεις ότι ένα σημαντικό μέρος αυτών των δύο ασφαλίστρων μπορεί να αποδοθεί σε αποζημίωση για κίνδυνο άλματος (βλέπε Santa-Clara και Yan (2010) και Bollerslev και Todorov (2011)). Παρόλα αυτά, ο τρόπος με τον οποίο ο κίνδυνος άλματος επηρεάζει τη διαστρωματική μεταβλητότητα των αποδόσεων των μετοχών έχει λάβει λιγότερη προσοχή από τη βιβλιογραφία. Έτσι λοιπόν, στο 2ο κεφάλαιο εξετάζουμε αν η έκθεση στα σοκ των καθοδικών (αριστερών) και ανοδικών (δεξιών) αλμάτων της αγοράς τιμολογείται στις αγορές. Σε ένα πρώτο βήμα κατασκευάζουμε ένα, θεωρητικά συνεπές, μέτρο του κινδύνου τυχαίων αλμάτων μέσω των δικαιωμάτων προαίρεσης του δείκτη S&P 500. Η μελέτη προσομοίωσης που πραγματοποιούμε δείχνει ότι το μέτρο αυτό παράγει αξιόπιστες εκτιμήσεις. Αντίθετα, οι αποδόσεις ενός χαρτοφυλακίου δικαιωμάτων που πρότειναν οι Cremers, Halling and Weinbaum (2015) παράγει μεροληπτικές εκτιμήσεις αναφορικά με το πριμ του κινδύνου άλματος. Βρίσκουμε ότι τα βήτα στα σοκ των καθοδικών παράγουν ένα στατιστικά σημαντικό ασφάλιστρο κινδύνου -11.52% σε ετήσια βάση για την ίδια περίοδο που έγινε η εκτίμηση των βήτα, σε αντίθεση με τα βήτα στα σοκ των ανοδικών αλμάτων. Αυτή η στατιστικά σημαντική σχέση μεταξύ των βήτα στα σοκ των καθοδικών αλμάτων και τον αποδόσεων το μετοχών δεν οφείλεται στα σοκ της ουδέτερης ως προς τον κίνδυνο διακύμανσης και ασυμμετρίας. Επίσης δείχνουμε ότι παράγει στατιστικά σημαντικές μη-κανονικές αποδόσεις τον επόμενο μήνα από την περίοδο εκτίμησης των βήτα ενώ είναι ανθεκτικό σε διαφορετικές περιόδους εκτίμησης των βήτα όπως 9, 6 και 3 μήνες και σε διαφορετικές περιόδους διακράτησης του χαρτοφυλακίου όπως 3 και 6 μήνες.

Στο 3ο κεφάλαιο εξετάζουμε τις καμπύλες τεκμαρτής μεταβλητότητας που προκύπτουν από τις τιμές δικαιωμάτων προαίρεσης πριν τις ημέρες ανακοινώσεων κερδών των εταιρειών. Δείχνουμε ότι ένα ποσοστό αυτών γίνεται κοίλο, παίρνοντας ασυνήθιστες μορφές όπως W, S και ανάποδο U. Αυτό το χαρακτηριστικό, που παρατηρείται κυρίως σε δικαιώματα προαίρεσης με μικρή διάρκεια, συνεπάγεται μια ουδέτερη ως προς τον κίνδυνο κατανομή με δυο κορυφές για την τιμή της μετοχής. Αυτό σημαίνει ότι οι επενδυτές προβλέπουν ένα άλμα στην τιμή της μετοχής την ημέρα ανακοίνωσης των κερδών. Βρίσκουμε ότι οι κοίλες καμπύλες τεκμαρτής μεταβλητότητας όντως προβλέπουν μεγαλύτερες απόλυτες αποδόσεις των μετοχών την ημέρα ανακοίνωσης των κερδών και μεγαλύτερη μεταβλητότητα μετά την ανακοίνωση. Ωστόσο, οι αποδόσεις των straddles των μετοχών με κοίλες καμπύλες τεκμαρτής μεταβλητότητας είναι σημαντικά χαμηλότερες από τις αποδόσεις των straddles των μετοχών με μη-κοίλες καμπύλες τεκμαρτής μεταβλητότητας. Αυτό οφείλεται στο ότι τα at-the-money δικαιώματα προαίρεσης των κοίλων καμπυλών είναι πολύ πιο ακριβά και τα άλματα στην τιμή της μετοχής την ημέρα της ανακοίνωσης των κερδών δεν είναι αρκετά μεγάλα για να αντισταθμίσουν το κόστος των δικαιωμάτων προαίρεσης. Οπότε οι επενδυτές εντοπίζουν τις ανακοινώσεις κερδών που προκαλούν άλματα στις τιμές των μετοχών και πληρώνουν σημαντικά μεγαλύτερο ασφάλιστρο κινδύνου για να αντισταθμίσουν αυτό τον κίνδυνο.

Abstract

This thesis focuses on examining the information contained in options about the valuation of equity securities. Options incorporate valuable information about investors' expectations on future returns of their underlying securities. This stems from the fact that markets are imperfect due to constraints such as asymmetric information and barriers to short selling, making options non-redundant assets.

Over the last decade there have been many studies deriving a measure from option contracts and examining whether it predicts future stock returns. For example, Guo and Qui (2014) find a negative relation between implied volatility and future stock returns and Stilger Kostakis and Poon (2017) show that risk-neutral skewness positively predicts future stock returns. The aforementioned studies use a measure based on a single property/moment of the risk-neutral distribution of stock returns and therefore may lose valuable information. In chapter 1 we propose a joint measure of the probability density function of stock returns. More specifically, we combine volatility, skewness and kurtosis implied by options in a score variable based on investors' moment preferences, that is, a low score identifies a stock with high volatility, low skewness and high kurtosis. On the contrary, a high score identifies a stock with low volatility, high skewness and low kurtosis. Essentially, our measure can be interpreted as a defensiveness measure where the definition of defensiveness is expanded by incorporating skewness and kurtosis alongside with volatility.

We sort stocks in portfolios based on our score measure and find that high score stocks have higher returns than low score stocks. This statistically significant relation between our score measure and future stock returns holds various robustness tests such as double sorts, Fama-MacBeth regressions and using a sample with larger cap stocks. We show that this relation is explained by the exposure to shocks in aggregate volatility and depends on investors' sentiment. In periods of low sentiment, the intertemporal capital asset pricing model (ICAPM) fully explains this relation, while in periods of high sentiment the relation remains statistically significant and is attributed to mispricing.

The literature has shown that jump risk is priced by investors in the options market. A part of the research has examined the impact of jump risk on equity and variance risk premiums, providing strong evidence that an important fraction of those premiums can be attributed to the jump risk premium (see Santa-Clara and Yan (2010) and Bollerslev and Todorov (2011)). Nevertheless, the way that jump risk impacts the cross-sectional variation of stock returns has received less attention in the literature. Therefore, in chapter 2 we examine if exposure to downside (left) and upside (right) jump shocks of the market are priced. We construct a theoretically consistent measure of jump risk through the S&P500 options. The simulation study we conduct shows that it provides reliable estimates as opposed to the JUMP risk factor of Cremers, Halling and Weinbaum (2015) which is a biased measure of jump risk. We find that betas to shocks in downside jumps produce a statistically significant risk premium of -11.52% contemporaneously in an annual basis, while betas on shocks to upside jumps do not. The statistically significant relation between betas to shocks in downside jumps and stock returns is not due to risk-neutral variance and skewness shocks. Additionally, we show that it produces statistically significant abnormal returns on the next month of the formation period while it is robust to different estimation period such as 9, 6 and 3 months and different holding periods such as 3 and 6 months.

In chapter 3 we examine the implied volatility curves that are arise from option prices prior to earnings announcements days. We show that a portion of them becomes concave, taking unusual shapes such as W, S, and inverted U. This characteristic, which is mostly observed in short-term options, implies a bimodal risk-neutral density for the stock price. This means that investors predict a jump in the stock price at the earnings announcement day. We find that concave implied volatility curves do predict higher absolute stock returns at the earnings announcement day and higher volatility after the earnings announcement day. However, straddle returns of stocks with concave implied volatility curves are statistically significantly lower than those with non-concave implied volatility curves. This is attributed to the fact that at-the-money options of concave implied volatility curves are much more expensive and the jumps of the stock price at the earnings announcement day are not large enough to offset the substantial cost of these straddles. Therefore, investors identify earnings announcements that make stock prices jump and pay a substantially higher premium to hedge against this risk.

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Introduction

It is widely accepted among academic and practitioners that option contracts contain valuable information of investors' expectations on future returns of the underlying asset. This happens because markets are incomplete in the real world due to limitations such as asymmetric information, transaction costs and short-sale restrictions, making options non-redundant assets. Recent papers have examined whether various option-implied variables predict future stock returns.

In this stream of research Guo and Qui (2014) find a negative relation between implied volatility and future stock returns. In their seminal work, An, Ang, Bali and Cakici (2014) show that innovations to option-implied call (put) volatility predict positive (negative) future stock returns. Rehman and Vilkov (2012), Stilger, Kostakis and Poon (2017), Gkionis et. al. (2018) and Borochin, Chang and Wu (2018), Chordia, Lin and Xiang (2020) find a positive relation between option-implied skewness and subsequent stock returns. Xing, Zhang and Zhao (2010) and Huang and Li (2019) examine the relation between the steepness of the implied volatility smirk and implied variance asymmetry (both being closely related to skewness), respectively, and future stock returns.

The above studies attribute the return predictability to informed trading, stressing that informed traders may choose the option market due to embedded leverage (Black (1975)) and limits to arbitrage mostly on the short side. On the contrary, Goncalves-Pinto et. al. (2020) indicate that stock return predictability related to options trading is driven by stock price pressure, rejecting the informed trading hypothesis. Moreover, Augustin and Subrahmanyam (2020) argue that it is hard to distinguish informed from speculative trading because researchers mostly do not observe the identity of traders.

Since observed option prices contain information for the probability density function of future stock returns, the use of a single measure measuring one particular property of this density may ignore valuable information for the return predictability of option prices. Therefore, in Chapter 1 we suggest a *joint* score measure tracking the probability density function of individual stock returns. This new measure is an intuitive score variable based on the volatility, skewness and kurtosis of future stock return distribution implied from option prices. A low level of it identifies a stock with high volatility, low skewness and high kurtosis. On the other hand, a high level of this measure identifies a stock with low volatility, high skewness and low kurtosis. Intuitively, this new measure ranks stocks based on investors' expectations about future stock return distribution properties and can be interpreted as a forward-looking defensiveness measure where the definition of defensiveness is expanded by incorporating skewness and kurtosis alongside with volatility. We find that high score stocks have higher returns than low score stocks. This statistically significant relation between our score measure and future stock returns holds various robustness tests. We show that this relation is explained by the exposure to shocks in aggregate volatility building on the intertemporal asset pricing (ICAPM). High score stocks are exposed to aggregate volatility innovations so that investors require a premium to hold them, while low score stocks hedge against shocks in aggregate volatility. Moreover, we document that this relation depends on investors' sentiment. In periods of low sentiment, the ICAPM fully explains the documented premium of the high-low score portfolio, while in periods of high sentiment the premium remains statistically significant and is also attributed to mispricing.

The option pricing literature provides strong evidence that aggregate jump risk is priced by investors in the options market. In fact, it is widely accepted that jumps should be included in option pricing models. A second stream of research examines the impact of jump risk in the time-series variation of equity and variance risk premiums, providing strong evidence that a significant fraction of these two premiums can be attributed to compensation for jump risk (see Santa-Clara and Yan (2010) and Bollerslev and Todorov (2011)). Despite the importance of jump risk documented in the literature, the investigation of how it affects the cross-section of expected stock returns has received less attention in the literature.

In Chapter 2 we demonstrate a model-free relation between the first and second-order moments of the log-return risk-neutral distribution which may be used to approximate the third-order moment of the jump process. As the first two moments can be extracted from option prices, it is straightforward to obtain an approximation of the third-order moment of the jump process from option prices. In addition, we provide theoretical and empirical evidence showing that the third-order moment of the jump process is strongly related to the spot (and expected integrated) variance. Thus, its innovations are affected from both volatility and jump risk. To this end, we suggest a new measure of jump risk exposure by scaling the third-order moment of the jump process with expected integrated variance. Theoretically, this new scaled variable is not related to the dynamics of spot variance, and its innovations can be considered as a proxy of jump risk.

We estimate jump risk loadings at the individual stock level using daily returns. We then sort stocks on the realized jump risk loadings, and we investigate whether stocks with higher betas have lower average returns contemporaneously, simultaneously controlling for other risk factors. In addition, we investigate the relation between realized jump-risk betas and future stock returns. Our main result is that jump risk is priced in the cross-section of stock returns, identifying a negative market price of jump risk, consistent with theory. We document that stocks with high jump risk loadings significantly underperform stocks with low ones contemporaneously, producing a statistically and economically significant premium of -9.41% per year at the 1% level. Besides investigating the pricing of aggregate jump risk in the cross-section of stock returns, it is also interesting to decompose jump risk innovations in their upside and downside components and examine the relative contribution of these two in the documented jump risk premium. The results of this exercise clearly show that the negative jump risk premium is due to its downside jump risk component. On the other hand, the premium of the high-low portfolio sorted by upside jump risk betas is not significant. Finally, our results hold to a predictive setting, in which we compare the subsequent realized monthly returns of the quintile portfolios sorted by jump risk betas estimated over the previous period. We show that the high-low quintile portfolio delivers significant risk-adjusted returns in the following month of the portfolio formation period. These results are robust to different beta estimation windows and return holding periods.

Quarterly earnings announcements are important scheduled corporate events that disseminate substantial fundamental information to investors about the company. A voluminous literature has examined a number of features related to these events, such as the behavior of stock returns (Ball and Brown (1968), Beaver (1968); Ball and Kothari (1991) Frazzini and Lamont (2007)) and systematic risk (Patton and Verardo (2012) Savor and Wilson (2016)) around these announcements. Literature on options has examined the behavior of equity option prices and implied volatilities (IVs) around earnings announcement days (EADs), identifying three stylized features. First, at-the-money (ATM) IV tends to increase in the runup to the EAD, as uncertainty increases before this information event, and second, ATM IV sharply decreases right after the announcement, when uncertainty is resolved (Patell and Wolfson (1979)). More recently, Dubinsky et al. (2019) documented that the term structure of ATM IV becomes downward sloping prior to EADs, meaning that ATM IV is higher for options with shorter expiries than for options with longer expiries.

Building upon this literature, Chapter 3 documents a novel feature with implications for our understanding of the behavior of stock prices, the pricing of earnings risk and the informational content of option prices. We show that a large fraction of IV curves extracted from short-expiry equity options *systematically* become concave in the run up to EADs. In our sample of very large and liquid firms, we find that up to 37.4% of IV curves exhibit concavity just before the announcement during the period 2013-2019. The concave IV curves we document are typically inverse U-shaped, S-shaped, or W-shaped. These shapes are in stark contrast with the convex volatility "smiles" and "smirks" that are commonly observed for equity options. Interestingly, the feature of concavity mostly disappears right after the announcement, as the uncertainty about this event is resolved, and the IV curve reverts to its standard convex shape.

We show that a concave IV curve reflects a bimodal risk-neutral distribution (RND) for the underlying stock price. Bimodality in the central part of the RND indicates that, the prevailing stock price will most likely be around either of the two identified modes. Hence, a bimodal RND reveals movements that can be considered as anticipated jumps in the continuous-time path of the underlying stock price. To this end, we argue that a concave IV curve provides a clear option-based signal of impending event risk for the underlying stock.

Moreover, concavity appears in short- rather than long-expiry options. We find that concave IV curves do predict higher absolute stock returns at the earnings announcement day and higher volatility after the earnings announcement day. However, straddle returns of stocks with concave IV curves are lower than those with non-concave IV curves. This is attributed to the fact that at-the-money options of concave IV curves are much more expensive and the jumps of the stock price at the earnings announcement day are not large enough to offset the substantial cost of these straddles. Therefore, investors identify earnings announcements that make stock prices jump and pay a substantially higher premium to hedge against this risk compared to other stocks.

This thesis is organized as follows. Chapter 1 constructs the score measure and examines its stock return predictability. Chapter 2 investigates the cross-sectional pricing of stocks according to sensitivities to option-implied jump risk. Chapter 3 documents that IV curves become concave prior to earnings announcements and examines the implications of this feature. The last section derives the conclusions of this thesis.

Chapter 1

Option-implied moments and the cross-section of stock returns

1.1 Introduction

There is a broad consensus among academic and practitioners that option contracts contain valuable information of investors' expectations on future returns of the underlying asset. This stems from the fact that markets are incomplete in the real world due to limitations such as asymmetric information and short-sale restrictions, making options non-redundant assets. A considerable amount of recent studies have proposed various techniques to extract the probability distribution of the underlying asset return from option prices (see Figleswki (2018) for a review), while others examined the information embedded in the properties of this distribution to predict future stock returns.

In this stream of research Guo and Qui (2014) find a negative relation between implied volatility and future stock returns. An, Ang, Bali and Cakici (2014) show that innovations to option-implied call (put) volatility predict positive (negative) future stock returns. Rehman and Vilkov (2012), Conrad, Dittmar and Ghysels (2013), Stilger, Kostakis and Poon (2017), Gkionis et. al. (2018) and Borochin, Chang and Wu (2018), Chordia, Lin and Xiang (2020) examine the relation between option-implied skewness and subsequent stock returns. Conrad, Dittmar and Ghysels (2013) find a negative relation between option-implied skewness and future stock returns while all other studies find a positive relation, Rehman and Vilkov argue that Conrad, Dittmar and Ghysels (2013) dilute the option-implied information by averaging option-implied skewness over the last three months thus resulting in different results.

Xing, Zhang and Zhao (2010) and Huang and Li (2019) examine the relation between the steepness of the implied volatility smirk and implied variance asymmetry (both being closely related to skewness), respectively, and future stock returns. Bali and Hovakimian (2009) show that the call-put implied volatility spread strongly predicts future stock returns. Baltussen, Bekkum and Grient (2018) investigate the return predictability of volatility of implied volatility (which may capture higher-order moments). Park, Kim and Shim (2019) examine the relation between the convexity of the implied volatility curve and subsequent stock returns, while Kim, Kim and Park (2020) investigate the return predictability of the term structure of implied volatility curve. In a closely related paper, Bali, Hu and Murray (2017) investigate the relation between option-implied volatility, skewness and kurtosis and expected returns estimated from financial analysts' price targets.[1]

Most of the aforementioned studies attribute the return predictability to informed trading, stressing that informed traders may choose the option market due to the embedded leverage as firstly pointed out by Black (1975). On the other hand, Goncalves-Pinto et. al. (2020) indicate that stock return predictability related to options trading is driven by stock price pressure, showing that the implied volatility spread of Cremers and Weinbaum (2010) and the change in the implied volatility spread of An, Ang, Bali and Cakici (2014) stock return predictability is mainly driven by the first day return. Moreover, Augustin and Subrahmanyam (2020) argue that identifying informed option trading is a difficult task because researchers mostly do not observe the identity of traders and it is hard to distinguish informed from speculative trading.

In this stream of research, the standard approach used is to calculate a *single* measure from option prices and then to examine the return predictability of this measure. For example, this measure could be the implied volatility (see Guo and Qui (2014)), the steepness of the implied volatility smirk (see Xing, Zhang and Zhao (2010)), the volatility asymmetry (see Huang and Li (2019)), the convexity of the implied volatility curve (see Park, Kim and Shim (2019)) or the implied skewness (see Conrad, Dittmar and Ghysels (2013) and Stilger, Kostakis and Poon (2017), Chordia, Lin and Xiang (2020) inter alia). Since however option prices observed across

[1] See Giamouridis and Skiadopoulos (2010) and Christoffersen, Jacobs and Chang (2013) for a detailed literature review on option-implied information.

moneyness contain information for the probability density function of future stock returns, the use of a single measure measuring one particular property of this density may ignore valuable information for the return predictability of option prices.

The aim of this chapter is twofold. First, we suggest a novel approach to extract information from options based on a *joint* measure tracking the probability density function of individual stock returns. Second, we aim to examine the return predictability of it. This new measure is an intuitive score variable based on the volatility, skewness and kurtosis of future stock return distribution implied from option prices. By construction, it encompasses the information embedded in the three individual option-implied moments and thus, it can provide a parsimonious measure of investors' expectations about future stock returns. A low level of it identifies a stock with high volatility, low skewness and high kurtosis. On the other hand, a high level of this measure identifies a stock with low volatility, high skewness and low kurtosis. Intuitively, this new measure ranks stocks based on investors' expectations about future stock return distribution properties and can be interpreted as a forward-looking defensiveness measure where the definition of defensiveness is expanded by incorporating skewness and kurtosis alongside with volatility.[2] Therefore, a low level of this score will identify a stock that is expected to be riskier, while a high level will identify a stock that is expected to be safer.

We first estimate decile portfolios sorting all US stocks with traded options at a monthly frequency from 1996 to 2016 on the composite option-implied moment-based score measure (SCORE, henceforth). The highest decile includes stocks with the highest score implying "good" return distribution properties. We denote it as *Good* henceforth. On the other hand, the lowest decile includes stocks with the lowest score related to "bad" return distribution properties. We denote it as *Bad* henceforth. The value-weighted (equally-weighted) Good minus Bad (GMB, henceforth) portfolio yields a statistically and economically significant average return of 0.75% (0.79%) per month. The corresponding Fama-French five-factor alpha is equal to 0.51% (0.73%) per month, which is also statistically significant. The evidence suggests that good stocks outperform bad ones. This positive relation between SCORE and subsequent monthly returns is not driven by short-term stock price adjustment, it

[2] Novy-Marx (2016) notes that defensive equity strategies, which go long safe or defensive stocks and short risky or aggressive ones, are typically constructed sorting on volatility or beta.

holds even when we restrict our sample to large, liquid stocks and it is robust to controls of various cross-sectional effects, such as size, book-to-market, momentum, mispricing, profitability and idiosyncratic volatility.

The significant positive average return of the GMB portfolio is not consistent with the implications of standard moment preferences (see Arditti (1967), Scott and Horvath (1980) and Gollier and Pratt (1996), inter alia). One would expect a negative premium for the GMB portfolio as investors would require a higher expected return to hold stocks with undesirable return distribution properties. Considering that, this chapter aims to provide an alternative explanation for the documented positive premium of good vs bad stocks.

This explanation builds on Merton's (1973) Intertemporal CAPM (ICAPM) *conditional* on the level of investors' sentiment. This model assumes an intertemporal (or long-horizon) risk-averse investor who seeks to hedge against adverse shocks to the future investment opportunity set. In recent empirical works (see Barinov (2018), inter alia) changes in aggregate market volatility, proxied by VIX, are commonly used to capture adverse shocks in the investment opportunity set. In that context, we find that good stocks are exposed to shocks in aggregate volatility while bad stocks hedge against these shocks. Therefore, an ICAPM investor is willing to accept a lower or even negative return for bad stocks as they offer a hedge against the deterioration of the investment opportunity set proxied by shocks in VIX. This is in stark contrast with a static risk-averse investor who would require a premium to hold bad stocks. On the other hand, an ICAPM investor would ask for a positive premium to hold good stocks as they are exposed to adverse shocks in the future investment opportunity set.

Additionally, we show that the explanatory power of the ICAPM depends on the level of investors' sentiment (which can be considered as a measure of variation in the general tendency of mispricing). When sentiment is low, the ICAPM can completely explain the GMB portfolio positive premium for both underpriced and overpriced stocks. Therefore, the positive abnormal return of the GMB portfolio obtained under a static model (CAPM or Fama-French 5-factor model) is fully rationalized by an intertemporal asset pricing model. In contrast, in high sentiment periods the ICAPM alpha remains positive and significant. We complement our rational risk-based explanation with mispricing. We find that during high sentiment periods the positive

ICAPM alpha of the GMB portfolio within overpriced stocks is due to the subsequent underperformance of bad stocks, while within underpriced stocks it can be mostly explained by the subsequent overperformance of good stocks. These empirical findings, indicate that negative (positive) investors' expectations about future states of return for stocks perceived as overpriced (underpriced) may be reflected in the option-implied distribution, generating a low (high) SCORE, with stocks adjusting to this information over the next month yielding negative (positive) returns.

In summary, a rational intertemporal risk-based model explains why good stocks overperform bad ones, at least when investors' sentiment is low. When sentiment is high, the positive premium of the GMB portfolio is also driven by information flow from the options to the stock market for stocks perceived to be as relatively mispriced.

Our chapter contributes to the literature that examines the linkage between the options market and the stock market at firm level in several ways. First, we propose a new parsimonious measure gauging investors' expectations about future states of stock returns, and we examine its return predictability. The new variable encompasses the information content of implied volatility, skewness and kurtosis, used individually in previous studies (see Guo and Qui (2014), Xing, Zhang and Zhao (2010), Conrad, Dittmar and Ghysels (2013) and Stilger, Kostakis and Poon (2017), inter alia). Second, our empirical analysis indicates the existence of a robust positive relation between SCORE and subsequent stock returns. Third, we investigate a possible explanation for the documented relation. Contrary to a vast majority of existing studies (including Xing, Zhang and Zhao (2010), Stilger, Kostakis and Poon (2017), Huang and Li (2019), Park, Kim and Shim (2019) and Chordia, Lin and Xiang (2020), inter alia) that attribute the relation between an option-implied variable tracking a specific characteristic of the probability density function of the underlying stock return and subsequent stock returns to a flow of information from the options to the stock market and limits to arbitrage, we provide evidence supporting a risk-based explanation too. This is the first study, to the best of our knowledge, indicating that the price of aggregate volatility risk is reflected in the option-implied distribution of individual stocks. Fourth, we contribute to a recent growing literature that documents that various anomalies can be explained by their exposure to market volatility risk. Barinov (2018) and Barinov and Chabakauri (2019) show that lottery-like stocks (with high extreme past returns and large expected idiosyncratic skewness) and stocks with high idiosyncratic volatility, respectively, hedge against shocks in market volatility, thus explaining their low average returns. They both argue that this is because their growth options, that hedge against aggregate volatility risk, are more valuable and take a larger fraction of the firm value. This argument may also hold in our case as our empirical results indicate that bad stocks have high idiosyncratic volatility and lottery-likeness. Finally, our study is related to recent papers that examine the effect of investors' sentiment on the abnormal returns of various documented anomalies and risk factors. Stambaugh, Yu and Yuan (2012, 2015) find that the abnormal return of various anomalies is stronger in high sentiment periods. Shen, Yu and Zhao (2017) find that beta-sorted portfolios formed on macro-related factors earn average returns consistent with a risk-based explanation in low sentiment periods. In contrast when sentiment is high, the reverse sign of these average returns is attributed to sentiment-induced mispricing.

The rest of this chapter is organized as follows. Section 2 describes the data and the methodology used to construct SCORE. Section 3 provides the univariate portfolio-level analysis, and a battery of robustness checks. Section 4 provides an explanation of the documented GMB portfolio premium, and Section 5 concludes the chapter. The Appendix includes the definition of variables employed in the analysis and technical details of calculating volatility, skewness and kurtosis from option prices.

1.2 Data and Methodology

1.2.1 Data

For the empirical analysis, we get returns, market capitalization and prices for all ordinary common shares (share code 10 and 11) from the CRSP database. Stock option data are downloaded from Optionmetrics for the period January 1996 to April 2016. We use standardized option data from the volatility surface file in order to have the same maturity for our options every day. Accounting data are obtained from

Compustat. The returns on the market premium, SMB, HML, MOM, RMW and CMA factors are obtained from Kenneth French's online data library.[3]

We drop stocks with price below $5. We filter out stocks if there is zero option volume or zero option open interest for all option contracts on that day using regular option data and drop stocks when at least one of the delta/maturity combination has a dispersion measure larger than 0.2 as in Borochin, Chang and Wu (2018) and end up with a final sample of 342,689 stock options data observations.

Stocks with options have a tilt toward larger market capitalizations and our filters drop more illiquid stocks resulting in a final sample where only 4.64%, 14.57% and 46.81% of our stocks are below of the NYSE size 10, 20 and 50 percentiles, respectively.

1.2.2 A score measure based on option-implied moments

As a first step we calculate option-implied moments for the total log-return distribution of stock i at the end of each month t using out-of-the money (OTM) call and put option data with constant maturity of 1 month (see Bakshi, Kapadia and Madan (2003)). Using these moments, we compute the option-implied volatility (VOL), skewness (SKEW) and kurtosis (KURT) of the 1-month ahead return distribution. Details for computing VOL, SKEW and KURT can be found in Appendix B.

We aim to create a composite score measure to gauge the exposure of each stock to VOL, SKEW and KURT. This composite measure will rank stocks based on investors' expectations about their future return distribution properties. A low level of this score will identify a stock with potential adverse properties related to high VOL, low SKEW and high KURT, while a high level will identify a stock with favorable ones related to low VOL, high SKEW and low KURT. Intuitively, a high value of SCORE identifies a defensive (safe) stock, where the definition of defensiveness is expanded to include SKEW and KURT alongside with VOL. On the other hand, a low

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

value of SCORE identifies an aggressive (risky) stock. The expansion of defensiveness is justified given the enormous evidence of non-normal stock returns. Furthermore, the inclusion of KURT, generating negative alphas (unreported), in the score measure mitigates further concerns about an artificially constructed factor with a-priori positive returns (see Novy-Marx (2016)). To construct this score, we follow the methodology of Asness, Frazzini and Pedersen (2019). More specifically, we rank VOL, SKEW and KURT cross-sectionally in ascending order and then standardize it by subtracting its rank mean and dividing by its rank standard deviation. VOL and KURT are multiplied by -1 so that stocks are ranked according to moment preferences. Then we compute SCORE by averaging the previously calculated individual *z*-scores. A detailed description of the SCORE calculation is presented in Appendix A.

1.3 Empirical Results

1.3.1 Univariate portfolio-level analysis

Each month we form decile portfolios by sorting stocks on SCORE. The highest decile includes stocks with the highest score implying favorable distribution properties. On the other hand, the lowest decile includes stocks with the lowest score related to adverse characteristics of their distribution. Decile portfolios are well populated, having 140 stocks on average. Table 1 reports the time-series average of monthly value-weighted average stocks' characteristics (except for size which is equally-weighted) for each decile portfolio based on SCORE. The definition of each variable is provided in Appendix A. First, we observe that sorting on SCORE is not equivalent on sorting on VOL and/or idiosyncratic volatility (IVOL). The IVOL pattern of SCORE decile portfolios is not monotonic. For example, decile 2 includes stocks with lower IVOL than decile 10. Thus, the distribution of stocks based on SCORE is not dominated by the pattern of VOL (or IVOL). On the other hand, SKEW and KURT of SCORE decile portfolios exhibit a monotonic pattern. SKEW (KURT) increases (decreases) monotonically when moving from decile 1 to 10. The non-monotonic pattern of IVOL holds for most of the other stock characteristics.

Stocks in the bad (decile 1) portfolio have lower market values, higher betas, are more illiquid, less profitable, have higher MAX and lower MIN and are more mispriced from stocks in the other 9 decile portfolios. The differences however between these stocks' characteristics among deciles 2, 3, …, 10 are not always numerically significant or in some cases the pattern is reversed. For example, stocks in the good (decile 10) portfolio have higher betas, higher MAX, lower MIN, higher IVOL than stocks in decile 2. While SKEW increases monotonically across SCORE decile portfolios, SKEW and SCORE have opposite exposure to SIZE and MISP. In fact, recent studies show that low SKEW stocks exhibit higher market values and lower MISP score than high SKEW ones (see Stilger, Kostakis and Poon (2017) and Chordia, Lin and Xiang (2020), respectively). In contrast, the results of Table 1 indicate that bad stocks have lower market values and higher MISP score than good ones, a characteristic attributed to the volatility ranking.

To better grasp the relation between the SCORE measure and the shape of the implied volatility curve, Figure 1 shows the pooled average implied volatility per delta point for stocks in the bad (orange line) and good (blue dashed line) portfolio. Stocks in the bad portfolio exhibit an implied volatility "smirk", which is related to the expensiveness of OTM put options. This shape is also consistent with low negative SKEW and high KURT. In stark contrast, stocks in the good portfolio have an almost flat implied volatility curve, satisfying the predictions of the Black-Scholes model. Stated alternatively, this graph leads to the conclusion that good stocks have an option-implied distribution of future log-returns which is close to normality, whereas bad stocks have an option-implied distribution that strongly deviates from normality.

Next, we compute value-weighted and equally-weighted returns of the decile portfolios along with alphas and factor loadings which we present in Table 2. Good stocks tend to have higher average returns. The GMB portfolio has a value-weighted (equally-weighted) monthly average return of 0.75% (0.79%) which is economically and statistically significant at 1% level. The GMB portfolio has also significant Carhart (1997) (CAR) and Fama-French (2015) five-factor (FF5) alphas, with both short and long legs of the strategy contributing to the overall abnormal return. This is important if we consider the fact the many anomalies derive their profits from the short leg of the strategy (see Avramov, Chordia, Jostova and Philipov (2013)). The factor loadings of the FF5 model indicate that, while the market beta of the GMB portfolio is insignificant, this portfolio is negatively exposed to SMB and positively exposed to CMA and RMW factors. This is something to expect given the results of Table 1. Decile 10 portfolio includes large profitable stocks compared to stocks in decile 1 portfolio. The results of Table 2 highlight that stocks expected to be safer have higher abnormal returns than stocks expected to be riskier after controlling for size, B/M, profitability and investment.

From a portfolio management perspective, the GMB portfolio enhances the performance of the well-known defensive strategy sorting high VOL (or IVOL) stocks and holding low VOL (or IVOL) ones. In our sample, a value-weighted low – high VOL (IVOL) portfolio exhibits positive albeit insignificant average return mainly due to its high variability of returns (its monthly standard deviation is equal to 12% (9%)). The inclusion of SKEW and KURT substantially decreases its standard deviation to 4% generating a significant average return.

1.3.2 Robustness tests

This section provides several robustness tests of our main result reported in Table 2. Avramov, Chordia, Jostova and Philipov (2013) find that profits for various anomalies diminish across size groups while Lu and Murray (2019) state that "mispricing is likely to be small among liquid and large cap stocks". To this end, we also examine the performance of our spread portfolio using two subsamples: 1) dropping stocks that belong to the lowest size quintile using NYSE breakpoints, where these microcap firms account for the 14.57% of our sample and 2) using only large cap stocks (stocks that have market capitalization larger than the NYSE median) which account for the 53.19% of our sample. This exercise will indicate if a significant premium exists when small illiquid stocks are excluded from the sample. As a second robustness check we form portfolios based on SCORE using quintiles and terciles.

Table 3 presents results in the same way as Table 2 jointly for the two robustness checks. Results are weakening if we use less extreme breakpoints and if we use a sample with less small cap stocks as expected. However, the GMB portfolio continues to show a statistically significant premium at the 5% level in all eighteen cases, delivering a statistically and economically significant premium of 0.57% even in the strictly conservative case of the value-weighted 3-1 tercile portfolio using only large cap stocks. All alphas using equally-weighted returns are statistically significant while only the FF5 alpha using the value-weighted 5-1 quintile portfolio difference in large caps is insignificant at the 10% level. Thus, the GMB portfolio has significant premiums and alphas even when the sample includes only large liquid stocks. The significant premiums of the GMB portfolio formed using quintiles and terciles further indicates that our main findings are not generated by stocks with extreme high or low SCORE values.

In a third robustness check we split our sample into four style universes following Novy-Marx (2016): small growth (SG), small value (SV), large growth (LG) and large value (LV) using NYSE medians as breakpoints and examine the performance of the GMB portfolio formed using quintiles within each subsample. Table 4 reports the raw average returns and alphas of value-weighted portfolios across the four subsamples. We find that the GMB portfolio provides statistically significant positive raw and risk-adjusted returns at the 10% level in all cases.

In a fourth robustness check we examine if stocks with high (low) SCORE generate high (low) future stock returns after controlling for several known factors in the literature. To this end, we perform bivariate sorts on SCORE while controlling for market beta (BETA), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), reversal (REV), Amihud's (2002) illiquidity measure (ILLIQ), maximum daily return of the previous month (MAX) of Bali, Cakici and Whitelaw (2011), idiosyncratic volatility (IVOL) measured as in Ang, Hodrick, Xing and Zhang (2006), mispricing score (MISP) of Stambaugh, Yu and Yuan (2015), profitability (PROFIT) measured as in Fama and French (2015), gross profitability (GPROFIT) of Novy-Marx (2013), expected idiosyncratic skewness (EIS) of Boyer, Mitton and Vorkink (2010) and beta of market volatility innovations (β ΔVIX) measured as in Ang, Hodrick, Xing and Zhang (2006).

We first sort stocks based on the control variable in quintiles, then within each quintile we further sort stocks on SCORE in quintiles, resulting in a total of 25 portfolios. We average SCORE portfolios across the five quintiles from the first sort and we report the average return and alpha of the GMB portfolio. These results are shown in Table 5 using value-weighted (Panel A) and equally-weighted (Panel B) returns. The main conclusion drawn from this table is that the documented positive abnormal return of the GMB portfolio remains robust after controlling for all these variables, with all alphas being significant at the 5% level. More importantly, the GMB portfolio alphas remain statistically significant after controlling for well-known variables used to construct defensive strategies such as IVOL and BETA.

In addition to the portfolio-level analysis, we run firm-level Fama-MacBeth (1973) cross-sectional regressions of one month ahead stock returns on SCORE and the set of firm characteristics used in the bivariate sorts. Table 6 reports average slope coefficients and t-statistics in parentheses. For all econometric specifications the average slope coefficient on SCORE is positive and significant at the 1% level confirming our earlier results. Favorable (adverse) future return distribution properties are associated with high (low) subsequent stock returns after controlling for market beta, size, B/M, momentum, reversal, illiquidity, maximum daily return over the previous month, idiosyncratic volatility, mispricing, profitability, expected idiosyncratic skewness and beta of market volatility innovations. As a further robustness test, we repeat the Fama-MacBeth (1973) cross-sectional regressions for the two subsamples used previously (i.e., (1) dropping stocks that belong to the lowest size quintile, and (2) using only large cap stocks). The results of these two additional empirical exercises are similar to those reported in Table 6 and can be provided by the authors upon request.

Finally, to alleviate potential concerns about nonsynchroneity bias (see Battalio and Schultz (2006)), which may hold for a portion of our sample, we calculate SCORE using option-implied moments calculated one day before the end of month. Again, the portfolio sorted on SCORE exhibits positive and significant alphas. These results are available upon request.

1.3.3 Univariate portfolio-level analysis in short-term periods

As already documented both legs of the strategy contribute to the overall abnormal monthly return. This is important because it suggests that the GMB premium is not entirely driven by short sale constraints: the long side of the hedge portfolio earns positive abnormal returns that are large economically and statistically significant. The overperformance of good stocks may be however short-lived and the documented positive performance in monthly horizon might be earned in the first post-formation days.

To examine this issue, we compute value-weighted and equally-weighted returns of SCORE formed decile portfolios on the following day and week of the formation period (i.e., the last day of each month). These results are reported in Table 7. The table also reports the performance of SCORE formed decile portfolios in monthly horizon when we skip the first day and/or the first week after the formation period. The results of this table indicate that approximately one third of the monthly average raw return of the GMB portfolio is realized on the first trading day after the formation period. This average daily raw return, equal to 0.24%, is large both statistically and economically. The high positive return of the hedge portfolio is driven by the overperformance of good stocks. The FF5 alpha of the GMB portfolio, equal to 0.27% for value-weighted returns, is also statistically (t-stat = 4.71) and economically significant. In weekly horizon the GMB portfolio average returns and alphas are lower compared to those of the first trading day but still statistically significant (expect for value-weighted alphas). More importantly, in monthly horizon, even when the first day or the first week are excluded, GMB portfolios alphas are still positive and significant. Again, this is driven by the overperformance of good stocks. The average raw monthly value-weighted return of the good (decile 10) portfolio when the first day is excluded is 0.88%, significant at the 1% level (t-stat = 3.43). This is approximately equal to the 73% of the overall monthly return.

Overall, these results indicate that the positive monthly abnormal return of the GMB portfolio cannot fully be explained by its short-term performance, especially for the long leg of the strategy. Gkionis et. al. (2018) document that stocks with high SKEW have high subsequent stock returns, earned in the very short-term (typically overnight). On the other hand, Goncalves-Pinto et. al. (2020) indicate that stock return predictability related to options trading is driven by stock price pressure, the correction of which occurs on the next day. Our empirical findings indicate that this is not the case when stocks are sorted by combining VOL, SKEW and KURT to a single score measure. Good stocks have high subsequent returns that persist over the following month.

1.3.4 Long-term performance

Moreover, we investigate how long the predictability of our score measure lasts. That is, we examine the performance of the good, bad and GMB portfolios over subsequent months. Table C1 reports the results. We find that the GMB portfolio delivers statistically significant returns up to month t+5. The abnormal return predictability from month t+2 to month t+5 is entirely driven by the short leg of the strategy. This means the abnormal return of the long leg is present only in the first post formation month. This is somewhat expected given the asymmetry in limits to arbitrage.

1.4 An explanation of the GMB portfolio premium

In the section we aim to provide an explanation of the documented positive abnormal return of the GMB portfolio. It lies on Merton’s (1973) ICAPM conditional on the level of market-wide investors’ sentiment.

The risk-based (through the ICAPM) dimension of our explanation is motivated by our previous empirical findings showing that the GMB portfolio abnormal return holds its significance on the large cap subsample where one expects market frictions to be much smaller. In addition, Barinov (2018) and Barinov and Chabakauri (2019) show that the MAX and IVOL factors, respectively, can be explained by the ICAPM with an aggregate volatility risk factor. In particular, they indicate that stocks with high MAX and/or high IVOL have low average returns because they hedge against innovations in market volatility. They argue that this is due to their option-like equity hedging against aggregate volatility risk. Motivated by these findings we investigate if bad stocks have low average returns because they hedge against innovations in market volatility, while good stocks have high average returns because they exposed to unexpected increases in market volatility. Table 1 provides preliminary evidence supporting this argument as bad stocks tend to have high MAX and high IVOL.

The second dimension of our explanation is related to sentiment-related mispricing. Studies in behavioral finance suggest that when arbitrage is limited, noise trader sentiment can persist in financial markets and affect asset prices (see DeLong et. al. (1990), inter alia). Following Stambaugh, Yu and Yuan (2012) and Shen, Yu and Zhao (2017), we examine if market-wide sentiment affects the GMB premium. According to these authors the existence of time-varying investors' sentiment that impacts many assets in the same direction at the same time and short sale constraints that limit the ability of rational investors to exploit overpricing, generate abnormal risk-adjusted returns. Under this view, following high sentiment periods the positive GMB portfolio abnormal return might be also attributed to bad stocks which are overpriced and due to limits to arbitrage investors are reluctant or unable to short them generating negative average returns.

We examine the validity of our framework building on an ICAPM with an aggregate volatility risk factor and sentiment intercept dummies. We construct factor FVIX that proxies for market volatility innovations following Barinov (2018).[4] We then identify variations over time in the general tendency of mispricing in the market, following Stambaugh, Yu and Yuan (2015) and relying on the market-wide index of investors' sentiment constructed by Baker and Wurgler (2006).[5] We split our sample in high- and low-sentiment months, where months with high (low) sentiment have the Baker-Wurgler sentiment index value at the end of the previous month above (below) its sample median. The ICAPM augmented with sentiment dummies is given as follows:

$$R_t = a_H d_H + a_L d_L + \beta_{MKT} MKT_t + \beta_{FVIX} FVIX_t + \varepsilon_t, \quad (1.1)$$

where R_t is the monthly excess return of the portfolios formed on SCORE. d_H and d_L are dummy variables indicating months with high and low sentiment, respectively.

[4] A number of studies suggest using shocks in aggregate volatility as a valid ICAPM state variable (see Campbell (1993), Chen (2002) and Ang et. al. (2006)). Chen (2002) indicates that such a risk factor is valid if it can predict future market volatility. Barinov (2018) shows that FVIX can indeed predict future market volatility and future recessions.

[5] Stambaugh, Yu and Yuan (2012) provide evidence that the Baker-Wurgler index identifies variation in mispricing.

MKT is the market excess return and FVIX is the aggregate volatility risk factor. If the GMB portfolio is exposed to innovations in market volatility, then we expect β_{FVIX} to be negative and significant. If in addition the ICAPM can explain the abnormal return of the GMB portfolio in low-sentiment months, then we expect a_L to be insignificant. In contrast, during high-sentiment months, where mispricing is more likely to occur, we might observe a_H to be positive and significant.

Table 8 reports the coefficient estimates of the previous model using value-weighted (Panel A) and equally-weighted (Panel B) returns. The empirical results of Table 8 support our implications. First, for the GMB portfolio, coefficient β_{FVIX} is negative and significant indicating that its positive abnormal return is related to its exposure to aggregate volatility risk. Second, for both value-weighted and equally-weighted returns coefficient a_L of the GMB portfolio is insignificant. In contrast a_H is positive and significant, providing evidence that the ICAPM cannot fully explain the abnormal return of the GMB portfolio when sentiment is high.[6] Additionally, this is mainly driven by the positive abnormal return of good stocks. Thus, the positive abnormal return of GMB portfolio in high-sentiment months is due to the overperformance of good stocks and not the underperformance of bad stocks as one might expect.

We further examine if the positive ICAPM alpha of the GMB portfolio during high-sentiment periods is related to the relative mispricing of stocks. To this end, we estimate the ICAPM with the sentiment dummies for the 9 tercile portfolios formed on SCORE and the mispricing measure MISP of Stambaugh, Yu and Yuan (2015). The results reported in Table 9 support our conjecture. After high sentiment periods, good stocks in the two lowest MISP terciles (i.e., stocks considered as relatively underpriced) tend to have positive and significant ICAPM alpha α_H. This significant positive abnormal return of good stocks contributes to the overperformance of the GMB portfolio for stocks considered as relatively underpriced following high market sentiment. On the other hand, for overpriced stocks the significant ICAPM alphas after high sentiment can be mainly attributed to the underperformance of bad stocks. Finally, note that in low-sentiment months the ICAPM alpha α_L of the GMB portfolio

[6] Unreported results, which can be provided by the authors upon request, indicate that the full sample ICAPM alpha is equal to 0.38% (t-stat = 1.47) for value-weighted, and 0.56% (t-stat = 2.86) for equally-weighted returns.

is insignificant across all MISP terciles indicating that the ICAPM explains the positive GMB portfolio premium irrespective of stocks relative mispricing.

The conclusion drawn by this section is that during low sentiment periods the ICAPM completely explains the positive abnormal return of the GMB portfolio. This is because the model captures the exposure of this portfolio to aggregate volatility risk. Therefore, the positive abnormal return of the GMB portfolio obtained under a static model (CAPM or Fama-French 5-factor model) is fully rationalized by the ICAPM. When sentiment in the market is high however, the ICAPM cannot fully explain the GMB portfolio premium. Within overpriced stocks this can be mostly explained by the underperformance of bad stocks, while for underpriced ones this is driven by the overperformance of good stocks.

Thus, in high-sentiment months good stocks considered as underpriced in the first place provide positive ICAPM alphas. One might argue that these positive abnormal returns may reflect a flow of information revealed in the options market about favorable future return distribution properties driving investors to buy them, thus generating positive returns on the subsequent month. However, the adjustment of stock prices to this information is not immediate as the analysis of Section 3.3 has also revealed pointing towards limited market efficiency at least for underpriced stocks during high sentiment periods.[7]

Another possible explanation for the positive abnormal return of the GMB portfolio lies on the theory of leverage aversion suggested by Black (1972) and Frazzini and Pedersen (2014). According to this explanation some investors are constrained or reluctant to use leverage and thus overweight risky securities (i.e., bad stocks) increasing their prices and decreasing their expected returns. In contrast, the safer assets (i.e., good stocks) are underweighted by these investors and thus trade at low prices, offering high expected returns. Though we cannot entirely rule out this explanation, our empirical results indicate that leverage constraints, if present, would affect the GMB portfolio return only in high sentiment periods. In fact, one would expect the opposite, that is, leverage constraints to manifest themselves in portfolio returns when sentiment is low, where investors would be reluctant to borrow stocks.

[7] Our conclusion agrees with Asness, Frazzini and Pedersen (2019) who also attribute the positive abnormal return of high-quality stocks to limited market efficiency.

Finally, we examine if the conditional CAPM can explain the positive premium of the GMB portfolio. If time-varying betas of the GMB portfolio are higher in recessions than in expansions, then investors would require a premium to be compensated against increased risk during recession periods. Following Petkova and Zhang (2005) we assume that the expected market risk premium and the conditional beta are linear functions of the four commonly used business cycle variables, i.e., the dividend yield, the default spread, the 1-month Tbill, and the term spread. We find that the conditional CAPM alpha of the GMB decile portfolio is equal to 0.70% for value-weighted and 0.83% for equally-weighted returns, both being statistically and economically significant. These significant alphas can be explained by the fact that the time-varying beta is lower (not higher) during recessions than expansions, due to the increase in the market beta of bad stocks decile portfolio. The last empirical finding is also consistent with Eisdorfer and Misirli (2019) indicating that distressed stocks increase their betas during bear market regimes.

1.5 Conclusions

Sorting stocks using only one moment can ignore important information about the impact of the whole distribution on the cross-sectional variation of future stock returns. In this chapter we create a new score measure, combining VOL, SKEW and KURT. A low level of it identifies a stock with high VOL, low SKEW and high KURT. On the other hand, a high level of it identifies a stock with low VOL, high SKEW and low KURT. A portfolio going long the highest decile (good) portfolio and short the lowest decile (bad) portfolio yields a statistically significant 0.75% (0.79%) value-weighted (equally-weighted) return and significant alphas, with both legs of the strategy contributing to the overall abnormal return. This positive relation between SCORE and subsequent monthly returns holds even when we restrict our sample to large, liquid stocks and it is robust when controlling for various variables in dependent bivariate sorts and Fama-MacBeth (1973) regressions.

As the significant positive average return of the GMB portfolio is not consistent with standard moment preferences this chapter aims to provide an explanation for it. This explanation builds on the ICAPM including the market and the aggregate volatility risk factors conditional on the level of investors' sentiment. We find that good stocks are exposed to shocks in aggregate volatility while bad stocks hedge against these shocks. Additionally, we show that the explanatory power of the ICAPM depends on the level of investors' sentiment. When investors' sentiment is low, the ICAPM can fully explain the GMB portfolio positive premium for both underpriced and overpriced stocks. In contrast, in high sentiment periods the ICAPM alpha remains positive and significant. Therefore, we complement a rational risk-based explanation with mispricing. We find that during high sentiment periods the positive ICAPM alpha of the GMB portfolio within overpriced stocks is due to the subsequent underperformance of bad stocks, while within underpriced stocks it can be mainly attributed to the subsequent overperformance of good stocks. Therefore, the positive premium of the GMB portfolio is also driven by information flow from the options to the stock market for stocks perceived to be as relatively mispriced.

Figure 1.1. Implied Volatility curves

This Figure shows the pooled average implied volatility curves across deltas for stocks in the bad (orange line) and good (blue dashed line) portfolio.

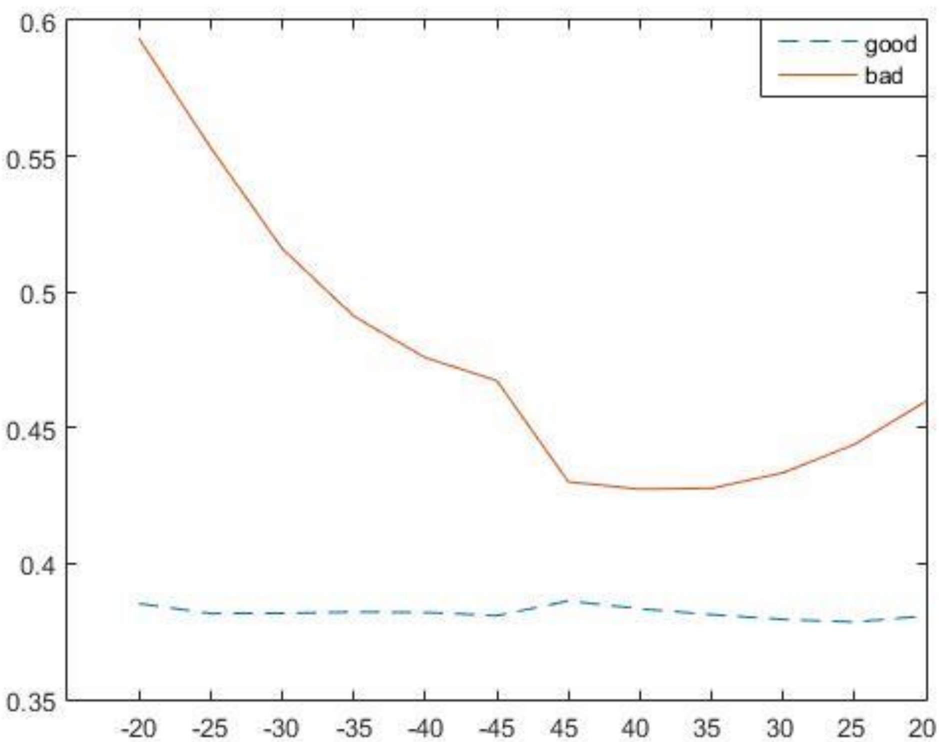

Table 1.1: Summary statistics for decile portfolios of stocks sorted by SCORE

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure computed from VOL, SKEW and KURT. Portfolio 1 includes stocks with the lowest SCORE (bad) and portfolio 10 contains stocks with the highest SCORE (good). This table shows the time-series average of monthly value-weighted stock characteristics (except for size which is equally-weighted) for each decile portfolio. The definition of each variable is provided in Appendix A.

	SCORE decile portfolios									
	Bad	2	3	4	5	6	7	8	9	Good
VOL	11.91	8.98	8.89	9.20	9.50	9.85	9.95	9.95	9.67	8.97
SKEW	-0.81	-0.70	-0.57	-0.48	-0.42	-0.36	-0.30	-0.24	-0.17	-0.08
KURT	4.44	4.16	3.91	3.78	3.70	3.65	3.62	3.61	3.60	3.50
BETA	1.11	0.92	0.93	1.00	1.03	1.06	1.08	1.07	1.03	0.95
SIZE	21.05	21.52	21.50	21.47	21.43	21.39	21.36	21.40	21.49	21.77
B/M	0.51	0.41	0.37	0.38	0.39	0.39	0.39	0.41	0.42	0.42
MOM	17.03	20.49	19.31	20.84	22.26	23.19	22.74	22.38	20.59	17.72
ILLIQ	0.18	0.08	0.06	0.06	0.07	0.07	0.08	0.08	0.08	0.07
ln(PRICE)	3.50	3.85	3.92	3.90	3.89	3.87	3.84	3.84	3.84	3.88
MAX	5.20	4.05	4.05	4.18	4.35	4.53	4.56	4.51	4.32	4.14
MIN	-4.29	-3.38	-3.47	-3.65	-3.78	-4.01	-4.08	-4.09	-4.03	-3.79
IVOL	1.64	1.29	1.30	1.37	1.44	1.52	1.54	1.55	1.52	1.44
MISP	48.83	43.78	42.60	41.95	42.75	42.67	42.60	43.04	42.88	42.07
EIS	0.65	0.59	0.59	0.58	0.59	0.58	0.59	0.59	0.60	0.61
PROFIT	0.30	0.40	0.45	0.45	0.41	0.38	0.43	0.37	0.39	0.42
GPROFIT	0.29	0.32	0.33	0.34	0.34	0.35	0.34	0.34	0.34	0.34

Table 1.2: Value-weighted and equally-weighted portfolios of stocks sorted by SCORE

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure computed from VOL, SKEW and KURT. Portfolio 1 includes stocks with the lowest SCORE (bad) and portfolio 10 includes stocks with the highest SCORE (good). The last column reports the performance of the good minus bad (GMB) portfolio. The table reports average monthly returns the following month, factor loadings, and alphas from the Carhart (1997) model (CAR), and factor loadings and alphas from the Fama and French (2015) 5-factor model (FF5). Panel A shows value-weighted returns and Panel B shows equally-weighted returns. Adj. R2 denotes the adjusted R-squared coefficient. MKT denotes the market risk premium factor, SMB is the size factor, HML is the value factor, MOM is the momentum factor, RMW denotes the operating profitability factor and CMA is the investment factor. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

Panel A: Value-weighted returns											
	SCORE decile portfolios										
	Bad	2	3	4	5	6	7	8	9	Good	GMB
Raw	0.47	0.66	0.42	0.74	0.92	0.76	0.98	1.01	0.98	1.21	0.75
	(1.11)	(2.14)	(1.41)	(2.17)	(2.72)	(2.29)	(2.88)	(3.14)	(3.07)	(4.47)	(2.60)
CAR	-0.35	-0.08	-0.25	-0.05	0.13	-0.05	0.18	0.28	0.22	0.50	0.84
	(-1.96)	(-0.72)	(-2.47)	(-0.51)	(1.42)	(-0.41)	(1.43)	(1.64)	(1.77)	(3.63)	(3.19)
MKT	1.05	0.93	0.91	1.07	1.06	1.04	1.04	1.01	0.98	0.89	-0.15
	(19.68)	(31.39)	(30.97)	(41.38)	(37.99)	(24.68)	(27.61)	(21.96)	(26.55)	(24.61)	(-2.04)
SMB	0.32	-0.02	-0.09	-0.05	-0.05	0.02	0.05	-0.02	-0.02	-0.19	-0.51
	(4.94)	(-0.40)	(-2.09)	(-0.88)	(-1.13)	(0.50)	(0.91)	(-0.22)	(-0.51)	(-3.51)	(-4.75)
HML	0.15	-0.05	-0.05	-0.05	-0.02	-0.12	0.07	-0.12	0.05	0.17	0.02
	(1.24)	(-1.12)	(-1.47)	(-1.09)	(-0.57)	(-1.77)	(0.90)	(-2.58)	(0.67)	(2.00)	(0.12)
MOM	-0.15	0.07	-0.03	0.01	0.01	0.09	-0.01	-0.03	0.01	0.04	0.19
	(-3.41)	(2.62)	(-1.47)	(0.45)	(0.45)	(2.64)	(-0.19)	(-0.61)	(0.17)	(0.98)	(2.51)
Adj. R2	82.98	85.54	87.62	89.13	87.77	87.51	84.52	83.02	83.74	77.89	29.57
FF5	-0.23	-0.04	-0.30	-0.05	0.14	0.02	0.10	0.17	0.14	0.28	0.51
	(-1.49)	(-0.32)	(-2.83)	(-0.48)	(1.17)	(0.20)	(0.78)	(1.09)	(1.13)	(2.48)	(2.50)
MKT	1.00	0.91	0.94	1.07	1.06	1.01	1.08	1.06	1.02	0.99	-0.01

	(23.27)	(26.29)	(31.61)	(34.13)	(28.57)	(27.20)	(33.91)	(24.66)	(29.22)	(32.24)	(-0.10)
SMB	0.21	-0.04	-0.10	-0.08	-0.02	0.03	0.07	0.04	0.05	-0.06	-0.27
	(3.80)	(-0.84)	(-2.20)	(-1.56)	(-0.56)	(0.61)	(1.25)	(0.63)	(0.95)	(-1.38)	(-3.42)
HML	0.36	-0.11	-0.06	-0.08	0.00	-0.16	-0.03	-0.16	0.00	-0.02	-0.38
	(2.79)	(-1.58)	(-1.37)	(-1.41)	(0.05)	(-1.93)	(-0.47)	(-2.20)	(-0.01)	(-0.45)	(-2.45)
RMW	-0.30	-0.04	0.02	-0.05	0.05	-0.01	0.07	0.16	0.18	0.37	0.67
	(-3.29)	(-0.63)	(0.49)	(-0.68)	(0.96)	(-0.15)	(1.11)	(2.23)	(2.62)	(5.52)	(5.06)
CMA	-0.26	0.11	0.06	0.13	-0.09	0.00	0.16	0.01	-0.02	0.22	0.48
	(-1.87)	(1.15)	(0.87)	(1.43)	(-0.80)	(-0.03)	(1.55)	(0.07)	(-0.20)	(2.36)	(2.42)
Adj. R2	82.66	85.08	87.57	89.32	87.83	86.67	84.79	83.25	84.26	80.60	35.79

Panel B: Equally-weighted returns

	SCORE Decile portfolios										
	Bad	2	3	4	5	6	7	8	9	Good	GMB
Raw	0.52	0.46	0.61	0.62	0.71	0.84	1.01	0.92	1.09	1.31	0.79
	(1.28)	(1.11)	(1.35)	(1.36)	(1.62)	(1.85)	(2.34)	(2.17)	(2.82)	(3.84)	(4.35)
CAR	-0.39	-0.46	-0.30	-0.33	-0.23	-0.10	0.11	0.02	0.22	0.50	0.89
	(-3.76)	(-4.59)	(-2.55)	(-2.93)	(-2.40)	(-1.12)	(0.96)	(0.23)	(1.71)	(3.82)	(5.98)
MKT	1.05	1.13	1.17	1.23	1.21	1.25	1.19	1.18	1.11	0.96	-0.09
	(34.15)	(32.05)	(33.65)	(36.08)	(51.53)	(41.90)	(38.01)	(39.77)	(34.94)	(29.62)	(-2.52)
SMB	0.67	0.57	0.66	0.72	0.71	0.65	0.65	0.56	0.40	0.27	-0.40
	(13.04)	(15.95)	(15.66)	(18.39)	(19.99)	(10.11)	(9.15)	(6.31)	(3.78)	(3.28)	(-5.38)
HML	0.29	0.04	-0.16	-0.17	-0.16	-0.16	-0.10	-0.01	0.15	0.31	0.02
	(6.82)	(0.95)	(-3.92)	(-4.60)	(-5.56)	(-3.73)	(-2.05)	(-0.16)	(2.88)	(4.31)	(0.30)
MOM	-0.12	-0.06	-0.10	-0.11	-0.10	-0.11	-0.16	-0.16	-0.14	-0.08	0.05
	(-3.50)	(-1.90)	(-2.75)	(-3.52)	(-4.43)	(-5.65)	(-6.07)	(-5.15)	(-4.44)	(-2.36)	(1.31)
Adj. R2	92.95	93.79	94.13	93.72	95.58	95.43	93.73	93.09	89.91	88.06	35.44
FF5	-0.46	-0.43	-0.21	-0.23	-0.13	-0.04	0.10	-0.04	0.14	0.27	0.73

	(-4.17)	(-4.46)	(-1.86)	(-1.98)	(-1.39)	(-0.38)	(0.83)	(-0.30)	(1.05)	(2.43)	(5.17)
MKT	1.09	1.11	1.14	1.19	1.16	1.22	1.20	1.22	1.15	1.07	-0.02
	(33.65)	(30.81)	(33.27)	(35.77)	(46.08)	(35.94)	(37.04)	(30.86)	(27.16)	(34.07)	(-0.54)
SMB	0.68	0.56	0.58	0.64	0.66	0.61	0.63	0.56	0.44	0.38	-0.30
	(11.36)	(12.33)	(9.85)	(14.10)	(16.23)	(11.03)	(9.65)	(7.73)	(5.13)	(6.89)	(-5.72)
HML	0.25	0.04	-0.10	-0.10	-0.08	-0.09	-0.03	0.03	0.19	0.16	-0.09
	(4.02)	(0.71)	(-1.72)	(-1.82)	(-1.86)	(-1.20)	(-0.37)	(0.37)	(1.99)	(2.34)	(-1.26)
RMW	0.00	-0.08	-0.25	-0.27	-0.20	-0.16	-0.11	-0.02	0.05	0.29	0.30
	(-0.09)	(-1.73)	(-3.91)	(-5.62)	(-3.93)	(-1.82)	(-1.17)	(-0.22)	(0.52)	(4.49)	(4.29)
CMA	-0.09	-0.13	-0.16	-0.18	-0.27	-0.24	-0.22	-0.17	-0.17	0.06	0.15
	(-1.36)	(-2.27)	(-2.48)	(-2.71)	(-4.43)	(-2.97)	(-2.03)	(-1.33)	(-1.34)	(0.77)	(2.09)
Adj. R2	92.54	93.93	94.18	93.76	95.74	95.38	92.95	92.15	89.23	89.44	39.34

Table 1.3: Value-weighted and equally-weighted portfolios of stocks sorted by SCORE using different breakpoints and sub-samples

Decile, quintile and tercile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure. The lowest decile, quintile or tercile portfolio includes stocks with the lowest SCORE (bad) and the highest decile, quintile or tercile portfolio includes stocks with the highest SCORE (good). The table reports average monthly returns the following month and alphas with respect to the Capital Asset Pricing Model (CAPM), the Fama and French (1993) 3-factor model (FF3), the Carhart (1997) model (CAR) and the Fama and French (2015) 5-factor (FF5) of the good minus bad (GMB) portfolio. Panel A shows results using the full sample. Panel B shows results after dropping all stocks in the lowest size quintile using NYSE breakpoints. Panel C shows results for all stocks with market cap above the NYSE median. GMB(d) denotes the good minus bad (GMB) decile portfolio, GMB(q) denotes the good minus bad (GMB) quintile portfolio and GMB(t) denotes the good minus bad (GMB) tercile portfolio. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

Panel A: Full sample						
	Panel A.1: Value-weighted			Panel A.2: Equally-weighted		
	GMB(d)	GMB(q)	GMB(t)	GMB(d)	GMB(q)	GMB(t)
Raw returns	0.75	0.51	0.56	0.79	0.71	0.58
	(2.60)	(2.61)	(3.96)	(4.35)	(4.97)	(4.17)
CAPM	0.92	0.56	0.57	0.89	0.77	0.62
	(3.57)	(2.80)	(3.68)	(5.25)	(5.60)	(4.40)
FF3	0.97	0.55	0.56	0.92	0.78	0.61
	(3.80)	(2.93)	(3.78)	(6.12)	(6.09)	(4.95)
CAR	0.84	0.53	0.54	0.89	0.79	0.63
	(3.19)	(2.77)	(3.50)	(5.98)	(5.81)	(4.75)
FF5	0.51	0.30	0.38	0.73	0.65	0.49
	(2.50)	(1.79)	(3.06)	(5.17)	(5.13)	(3.91)
Panel B: Dropping stocks with size in the lowest quintile						
	Panel B.1: Value-weighted			Panel B.2: Equally-weighted		
	GMB(d)	GMB(q)	GMB(t)	GMB(d)	GMB(q)	GMB(t)
Raw returns	0.70	0.52	0.57	0.79	0.69	0.57
	(2.39)	(2.69)	(4.13)	(4.15)	(4.60)	(4.01)
CAPM	0.88	0.58	0.58	0.89	0.75	0.61
	(3.30)	(2.88)	(3.83)	(5.01)	(5.20)	(4.27)
FF3	0.93	0.56	0.57	0.92	0.76	0.60
	(3.50)	(2.95)	(3.98)	(5.55)	(5.60)	(4.77)
CAR	0.80	0.54	0.55	0.86	0.76	0.62
	(2.94)	(2.76)	(3.71)	(5.34)	(5.35)	(4.58)
FF5	0.46	0.30	0.40	0.73	0.62	0.47
	(2.13)	(1.83)	(3.20)	(4.70)	(4.69)	(3.72)
Panel C: Dropping stocks with size below the median						
	Panel C.1: Value-weighted			Panel C.2: Equally-weighted		
	GMB(d)	GMB(q)	GMB(t)	GMB(d)	GMB(q)	GMB(t)
Raw returns	0.70	0.49	0.57	0.70	0.52	0.41
	(2.40)	(2.47)	(4.05)	(4.14)	(3.95)	(3.75)

CAPM	0.87	0.55	0.59	0.79	0.58	0.45
	(3.21)	(2.67)	(3.81)	(5.06)	(4.59)	(4.14)
FF3	0.91	0.53	0.58	0.83	0.60	0.46
	(3.32)	(2.65)	(3.89)	(5.14)	(4.56)	(4.12)
CAR	0.76	0.51	0.56	0.75	0.57	0.46
	(2.71)	(2.40)	(3.60)	(4.75)	(4.31)	(4.03)
FF5	0.41	0.25	0.38	0.61	0.40	0.28
	(1.86)	(1.43)	(2.99)	(4.08)	(3.31)	(2.71)

Table 1.4: Value-weighted portfolios of stocks sorted by SCORE across four style universes

Quintile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure. The lowest quintile portfolio includes stocks with the lowest SCORE (bad) and the highest quintile portfolio includes stocks with the highest SCORE (good). We split our sample into four style universes: small growth (SG), small value (SV), large growth (LG) and large value (LV) using NYSE medians as breakpoints. The table reports average monthly returns the following month and alphas with respect to the Capital Asset Pricing Model (CAPM), the Fama and French (1993) 3-factor model (FF3), the Carhart (1997) model (CAR) and the Fama and French (2015) 5-factor (FF5) of the good minus bad (GMB) value-weighted portfolio. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

	Raw		CAPM		FF3		CAR		FF5	
SG	0.86	(3.13)	0.92	(3.52)	0.90	(3.62)	0.89	(3.50)	0.76	(2.89)
SV	0.79	(2.79)	0.86	(2.93)	0.85	(3.01)	0.78	(2.56)	0.72	(2.52)
LG	0.60	(2.84)	0.65	(2.92)	0.61	(2.88)	0.61	(2.73)	0.33	(1.73)
LV	0.47	(1.78)	0.50	(1.68)	0.63	(2.10)	0.62	(1.96)	0.56	(1.98)

Table 1.5: Double-sorted portfolios on SCORE after controlling for several variables

Double-sorted quintile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on SCORE after controlling for mispricing (MISP), idiosyncratic volatility (IVOL), momentum (MOM), book-to-market (B/M), reversal (REV), market capitalization (SIZE), market beta (BETA), maximum daily return of the previous month (MAX), profitability (PROFIT), gross profitability (GPROFIT), illiquidity (ILLIQ), expected idiosyncratic skewness (EIS) and beta of market volatility innovations (β ΔVIX). The definition of each variable is provided in Appendix A. We first sort stocks into quintiles using each one of these variables, then within each quintile, we sort stocks into quintiles based on SCORE. We average SCORE sorted portfolios across the five quintiles from the first sort and we report average monthly returns and alphas of the good minus bad (GMB) portfolio. Alphas are measured with respect to the Capital Asset Pricing Model (CAPM), the Fama and French (1993) 3-factor model (FF3), the Carhart (1997) model (CAR) and the Fama and French (2015) 5-factor (FF5). Panel A shows value-weighted returns and Panel B shows equally-weighted returns. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

Panel A: Value-weighted returns										
	Raw		CAPM		FF3		CAR		FF5	
BETA	0.54	(3.30)	0.60	(3.66)	0.63	(3.72)	0.62	(3.66)	0.45	(3.11)
SIZE	0.60	(4.34)	0.65	(4.85)	0.65	(4.97)	0.63	(4.69)	0.49	(4.13)
B/M	0.48	(3.34)	0.50	(3.28)	0.53	(3.26)	0.54	(3.12)	0.42	(2.72)
MOM	0.66	(4.68)	0.70	(4.79)	0.72	(5.08)	0.68	(4.88)	0.52	(4.41)
REV	0.59	(3.58)	0.68	(4.23)	0.68	(4.48)	0.67	(4.19)	0.50	(3.59)
ILLIQ	0.55	(4.62)	0.59	(5.00)	0.61	(5.02)	0.60	(4.98)	0.49	(4.01)
MAX	0.51	(3.36)	0.55	(3.57)	0.58	(3.89)	0.54	(3.57)	0.41	(3.09)
IVOL	0.76	(3.66)	0.86	(4.15)	0.87	(4.60)	0.81	(4.25)	0.64	(4.40)
MISP	0.59	(3.38)	0.65	(3.52)	0.65	(3.51)	0.60	(3.08)	0.44	(2.89)
PROFIT	0.65	(3.58)	0.73	(3.76)	0.71	(3.96)	0.69	(3.59)	0.44	(2.76)
GPROFIT	0.50	(3.01)	0.52	(2.93)	0.50	(3.18)	0.48	(3.00)	0.30	(2.06)
EIS	0.55	(3.16)	0.61	(3.30)	0.60	(3.57)	0.58	(3.46)	0.36	(2.47)
β ΔVIX	0.62	(3.72)	0.67	(3.93)	0.66	(3.99)	0.64	(3.82)	0.43	(3.16)
Panel B: Equally-weighted returns										
	Raw		CAPM		FF3		CAR		FF5	
BETA	0.61	(5.00)	0.65	(5.62)	0.67	(5.70)	0.66	(5.55)	0.58	(5.14)
SIZE	0.60	(4.64)	0.65	(5.21)	0.66	(5.20)	0.63	(4.85)	0.49	(4.41)
B/M	0.65	(4.69)	0.69	(5.13)	0.70	(5.64)	0.72	(5.54)	0.60	(4.76)
MOM	0.67	(5.63)	0.72	(6.10)	0.72	(6.64)	0.74	(6.66)	0.60	(5.70)
REV	0.68	(5.30)	0.75	(6.03)	0.76	(6.50)	0.75	(6.08)	0.64	(5.67)
ILLIQ	0.64	(4.94)	0.69	(5.49)	0.70	(5.52)	0.68	(5.25)	0.56	(4.69)
MAX	0.65	(6.13)	0.67	(6.41)	0.69	(6.50)	0.69	(6.15)	0.62	(5.91)
IVOL	0.66	(6.02)	0.69	(6.39)	0.72	(6.60)	0.69	(6.21)	0.63	(6.13)
MISP	0.58	(4.29)	0.62	(4.69)	0.63	(4.98)	0.64	(5.08)	0.51	(4.10)
PROFIT	0.66	(4.76)	0.71	(5.10)	0.71	(5.77)	0.70	(5.49)	0.59	(4.58)
GPROFIT	0.69	(4.34)	0.74	(4.65)	0.73	(5.30)	0.75	(5.16)	0.60	(4.26)
EIS	0.65	(5.04)	0.70	(5.61)	0.71	(6.15)	0.71	(5.90)	0.58	(4.86)
β ΔVIX	0.69	(5.17)	0.74	(5.65)	0.74	(6.11)	0.75	(5.74)	0.62	(5.24)

Table 1.6: Fama-MacBeth cross-sectional regressions

This table presents firm-level Fama-MacBeth (1973) cross-sectional regression results of one month ahead stock returns on SCORE and a set of firm characteristics for the sample period January 1996 to April 2016. The firm characteristics that we control for in the econometric specifications include market beta (BETA), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), reversal (REV), illiquidity (ILLIQ), maximum daily return of the previous month (MAX), idiosyncratic volatility (IVOL), mispricing (MISP), profitability (PROFIT), gross profitability (GPROFIT), expected idiosyncratic skewness (EIS) and beta of market volatility innovations (β ΔVIX). The definition of each variable is provided in Appendix A. All variables are winsorized at the 1% and 99% levels. The time-series average slope coefficients are reported in each row. Adj. R2 denotes the adjusted R-squared coefficient. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0062	0.0103	0.0125	0.0116	0.0106	0.0129	0.0159	0.0266	0.0247	0.0238	0.0270	0.0268
	(1.51)	(1.57)	(1.84)	(1.71)	(1.58)	(2.11)	(2.63)	(4.25)	(4.12)	(3.87)	(4.06)	(4.10)
SCORE	0.0057	0.0042	0.0043	0.0042	0.0043	0.0042	0.0041	0.0038	0.0038	0.0038	0.0036	0.0035
	(4.39)	(4.73)	(4.91)	(5.15)	(5.37)	(5.54)	(5.46)	(5.04)	(5.07)	(4.98)	(4.83)	(4.83)
BETA		0.0001	-0.0013	-0.0008	-0.0007	-0.0004	-0.0004	-0.0003	-0.0002	-0.0003	-0.0003	-0.0003
		(0.04)	(-0.63)	(-0.34)	(-0.32)	(-0.19)	(-0.18)	(-0.13)	(-0.10)	(-0.17)	(-0.13)	(-0.15)
SIZE		-0.0005	-0.0007	-0.0006	-0.0005	-0.0007	-0.0009	-0.0012	-0.0013	-0.0011	-0.0012	-0.0012
		(-0.75)	(-1.08)	(-0.99)	(-0.81)	(-1.11)	(-1.53)	(-2.10)	(-2.15)	(-2.05)	(-2.14)	(-2.17)
B/M		0.0014	0.0013	0.0019	0.0018	0.0015	0.0012	0.0011	0.0013	0.0017	0.0018	0.0016
		(0.63)	(0.58)	(0.85)	(0.81)	(0.71)	(0.56)	(0.51)	(0.56)	(0.73)	(0.79)	(0.73)
MOM			-0.0005	-0.0009	-0.0006	-0.0004	-0.0002	-0.0015	-0.0013	-0.0014	-0.0018	-0.0017
			(-0.19)	(-0.31)	(-0.22)	(-0.14)	(-0.06)	(-0.51)	(-0.47)	(-0.47)	(-0.61)	(-0.59)
REV				-0.0179	-0.0178	-0.0154	-0.0202	-0.0228	-0.0236	-0.0232	-0.0237	-0.0244
				(-2.55)	(-2.56)	(-2.02)	(-2.63)	(-2.90)	(-3.02)	(-2.96)	(-3.05)	(-3.18)
ILLIQ					-0.0387	-0.0270	-0.0181	-0.0150	-0.0007	-0.0094	0.0105	0.0109
					(-0.72)	(-0.50)	(-0.33)	(-0.26)	(-0.01)	(-0.17)	(0.20)	(0.21)
MAX						-0.0256	0.0304	0.0405	0.0400	0.0382	0.0399	0.0431
						(-1.41)	(1.44)	(1.95)	(1.94)	(1.87)	(1.98)	(2.15)
IVOL							-0.2192	-0.2093	-0.2041	-0.2055	-0.2101	-0.2153

							(-2.96)	(-2.77)	(-2.72)	(-2.73)	(-2.84)	(-2.88)
MISP								-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
								(-3.63)	(-3.24)	(-3.18)	(-3.21)	(-3.18)
PROFIT									0.0029			
									(1.40)			
GPROFIT										0.0028	0.0024	0.0024
										(1.01)	(0.89)	(0.86)
EIS											-0.0036	-0.0034
											(-1.96)	(-1.83)
β ΔVIX												-0.0009
												(-1.05)
Adj. R2	0.20%	5.37%	6.68%	7.43%	7.70%	8.12%	8.32%	8.66%	8.99%	9.07%	9.31%	9.53%

Table 1.7: Value-weighted and equally-weighted portfolios of stocks sorted by SCORE in short-term periods

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure. Portfolio 1 includes stocks with the lowest SCORE (bad) and portfolio 10 includes stocks with the highest SCORE (good). The last column reports the performance of the good minus bad (GMB) portfolio. The table reports average returns and alphas of the 5-factor model (FF5). Panel A shows value-weighted and equally-weighted returns one-day ahead of the formation period. Panel B shows value-weighted and equally-weighted returns one week ahead of the formation period. Panel C shows value-weighted and equally-weighted returns the following month after excluding the first day. Panel D shows value-weighted and equally-weighted returns the following month after excluding the first week. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

	SCORE decile portfolios										
	Bad	2	3	4	5	6	7	8	9	Good	GMB
	Panel A: One-day ahead returns										
	Panel A.1: Value-weighted										
Raw	0.11	0.10	0.18	0.24	0.19	0.23	0.23	0.23	0.28	0.35	0.24
	(0.94)	(1.15)	(2.03)	(2.53)	(2.04)	(2.31)	(2.31)	(2.31)	(3.10)	(4.20)	(3.83)
FF5	-0.14	-0.11	-0.03	0.04	-0.01	0.00	0.02	0.01	0.11	0.13	0.27
	(-3.46)	(-3.98)	(-1.03)	(1.23)	(-0.26)	(0.06)	(0.73)	(0.36)	3.44	(4.05)	(4.71)
	Panel A.2: Equally-weighted										
Raw	0.01	0.04	0.07	0.09	0.11	0.11	0.14	0.18	0.21	0.25	0.24
	(0.10)	(0.34)	(0.69)	(0.76)	(0.95)	(0.95)	(1.15)	(1.54)	(1.91)	(2.53)	(5.87)
FF5	-0.14	-0.09	-0.04	-0.02	0.00	-0.02	0.01	0.03	0.06	0.08	0.22
	(-5.46)	(-3.88)	(-2.02)	(-1.01)	(-0.04)	(-0.81)	(0.36)	(0.94)	(2.03)	(2.76)	(6.05)
	Panel B: One-week ahead returns										
	Panel B.1: Value-weighted										
Raw	0.16	0.19	0.33	0.41	0.36	0.39	0.39	0.37	0.39	0.37	0.21
	(0.78)	(1.24)	(1.96)	(2.16)	(1.97)	(1.91)	(1.73)	(1.82)	(1.91)	(1.99)	(1.97)
FF5	-0.14	-0.11	0.01	0.07	0.05	0.03	0.06	0.03	0.03	-0.03	0.11
	(-2.34)	(-1.67)	(0.18)	(1.26)	(1.00)	(0.47)	(0.94)	(0.51)	(0.41)	(-0.43)	(1.08)

Panel B.2: Equally-weighted											
Raw	0.04	0.12	0.20	0.21	0.19	0.24	0.29	0.30	0.31	0.33	0.29
	(0.18)	(0.53)	(0.83)	(0.82)	(0.76)	(0.91)	(1.10)	(1.19)	(1.38)	(1.60)	(3.65)
FF5	-0.19	-0.07	0.03	0.02	0.00	0.05	0.09	0.06	0.04	0.03	0.23
	(-2.94)	(-1.53)	(0.56)	(0.32)	(0.08)	(0.84)	(1.51)	(0.98)	(0.59)	(0.54)	(2.89)
Panel C: Monthly returns excluding the first trading day											
Panel C.1: Value-weighted											
Raw	0.39	0.56	0.25	0.50	0.74	0.55	0.76	0.79	0.71	0.88	0.49
	(1.01)	(1.98)	(0.90)	(1.65)	(2.39)	(1.79)	(2.48)	(2.68)	(2.44)	(3.43)	(1.88)
FF5	-0.12	0.03	-0.24	-0.05	0.15	-0.02	0.10	0.16	0.04	0.18	0.30
	(-0.78)	(0.25)	(-2.54)	(-0.47)	(1.45)	(-0.15)	(0.83)	(1.02)	(0.35)	(1.63)	(1.54)
Panel C.2: Equally-weighted											
Raw	0.53	0.43	0.54	0.55	0.63	0.75	0.89	0.76	0.91	1.08	0.55
	(1.44)	(1.15)	(1.31)	(1.33)	(1.55)	(1.80)	(2.27)	(1.98)	(2.56)	(3.51)	(3.26)
FF5	-0.29	-0.28	-0.12	-0.12	-0.05	0.05	0.17	0.00	0.15	0.26	0.54
	(-2.72)	(-3.13)	(-1.05)	(-1.17)	(-0.44)	(0.52)	(1.37)	(0.07)	(1.10)	(2.36)	(4.05)
Panel D: Monthly returns excluding the first week											
Panel D.1: Value-weighted											
Raw	0.34	0.49	0.11	0.33	0.58	0.41	0.62	0.65	0.62	0.87	0.54
	(1.08)	(2.16)	(0.50)	(1.41)	(2.48)	(1.74)	(2.75)	(3.08)	(2.93)	(4.65)	(2.21)
FF5	-0.13	0.04	-0.26	-0.09	0.06	-0.04	0.11	0.12	0.03	0.30	0.42
	(-0.92)	(0.36)	(-2.84)	(-1.01)	(0.69)	(-0.46)	(1.00)	(0.97)	(0.30)	(2.65)	(2.42)
Panel D.2: Equally-weighted											
Raw	0.52	0.37	0.43	0.44	0.56	0.66	0.78	0.66	0.82	1.01	0.49
	(1.76)	(1.25)	(1.29)	(1.37)	(1.71)	(2.01)	(2.52)	(2.21)	(2.98)	(4.52)	(3.12)
FF5	-0.24	-0.25	-0.18	-0.19	-0.06	0.05	0.12	-0.01	0.15	0.31	0.55
	(-2.45)	(-2.84)	(-1.83)	(-1.81)	(-0.57)	(0.47)	(0.97)	(-0.09)	(1.08)	(2.90)	(5.03)

Table 1.8: The ICAPM for stocks portfolios sorted by SCORE during periods of high and low investors' sentiment

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure. Low decile portfolio includes stocks with the lowest SCORE (bad) and high decile portfolio includes stocks with the highest SCORE (good). High (low) sentiment indicates a month in which the value of the Baker and Wurgler (2006) sentiment index at the end of the previous month is above (below) its sample median. The table reports ICAPM alpha a_H (a_L) in high (low) sentiment months, market beta β_{MKT} and beta of FVIX β_{FVIX}, for the good, the bad and the good minus bad (GMB) portfolios. Panel A shows value-weighted returns and Panel B shows equally-weighted returns. Adj. R2 denotes the adjusted R-squared coefficient. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

	Panel A: Value-weighted			Panel B: Equally-weighted		
	Bad	Good	GMB	Bad	Good	GMB
a_H	-0.16	0.47	0.62	-0.11	0.76	0.87
	(-0.68)	(2.36)	(1.78)	(-0.34)	(3.40)	(3.16)
a_L	-0.04	0.10	0.14	-0.07	0.19	0.26
	(-0.17)	(0.49)	(0.45)	(-0.34)	(0.99)	(1.32)
β_{MKT}	2.01	-0.01	-2.02	1.97	0.77	-1.20
	(8.99)	(-0.05)	(-4.70)	(5.59)	(2.42)	(-3.48)
β_{FVIX}	0.74	-0.71	-1.45	0.67	-0.20	-0.87
	(4.10)	(-3.29)	(-4.11)	(2.31)	(-0.79)	(-2.99)
Adj. R2	80.10%	76.67%	24.07%	80.58%	82.67%	23.14%

Table 1.9: The ICAPM for double-sorted MISP-SCORE portfolios during periods of high and low investors' sentiment

Double-sorted tercile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on SCORE after controlling for mispricing (MISP). We first sort stocks into terciles using MISP, then within each tercile, we sort stocks into terciles based on SCORE. High (low) sentiment indicates a month in which the value of the Baker and Wurgler (2006) sentiment index at the end of the previous month is above (below) its sample median. The table reports ICAPM alpha a_H (a_L) in high (low) sentiment months, market beta β_{MKT} and beta of FVIX β_{FVIX}, for the good, the bad and the good minus bad (GMB) portfolios across MISP terciles. Panel A shows value-weighted returns and Panel B shows equally-weighted returns. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

		Panel A: Value-Weighted			Panel B: Equally-Weighted		
		Bad	Good	GMB	Bad	Good	GMB
Most underpriced	a_H	-0.04	0.26	0.30	0.32	0.74	0.42
		(-0.24)	(1.13)	(0.93)	(1.24)	(3.73)	(2.28)
	a_L	0.02	0.21	0.20	0.25	0.27	0.02
		(0.13)	(1.33)	(0.86)	(1.31)	(1.86)	(0.13)
	β_{MKT}	0.36	0.31	-0.06	1.38	0.94	-0.44
		(1.90)	(1.35)	(-0.15)	(3.67)	(4.06)	(-1.62)
	β_{FVIX}	-0.35	-0.46	-0.11	0.32	-0.03	-0.34
		(-2.33)	(-2.53)	(-0.40)	(1.05)	(-0.16)	(-1.59)
Next 40%	a_H	-0.31	0.56	0.87	0.36	0.80	0.44
		(-2.21)	(2.83)	(3.27)	(0.96)	(3.24)	(1.29)
	a_L	-0.10	-0.12	-0.02	0.09	0.17	0.08
		(-0.63)	(-0.56)	(-0.05)	(0.43)	(0.89)	(0.38)
	β_{MKT}	1.24	0.32	-0.92	2.08	1.08	-1.00
		(6.21)	(1.00)	(-1.87)	(5.20)	(3.49)	(-1.77)
	β_{FVIX}	0.14	-0.54	-0.68	0.74	-0.05	-0.79
		(0.91)	(-2.03)	(-1.72)	(2.22)	(-0.20)	(-1.68)
Most overpriced	a_H	-0.66	-0.19	0.47	-0.47	0.10	0.57
		(-3.21)	(-0.77)	(1.62)	(-1.42)	(0.28)	(2.08)
	a_L	-0.57	-0.34	0.23	-0.28	-0.29	0.00
		(-1.79)	(-1.41)	(0.71)	(-0.97)	(-0.96)	(-0.01)
	β_{MKT}	1.65	0.75	-0.90	3.01	2.05	-0.96
		(4.23)	(1.93)	(-2.09)	(8.37)	(5.38)	(-2.68)
	β_{FVIX}	0.32	-0.29	-0.62	1.31	0.55	-0.77
		(1.14)	(-0.94)	(-1.84)	(4.50)	(1.78)	(-2.48)
All stocks	a_H	-0.30	0.36	0.66	-0.03	0.56	0.59
		(-3.51)	(2.76)	(3.48)	(-0.11)	(2.43)	(2.58)
	a_L	-0.17	0.10	0.27	0.01	0.12	0.11
		(-1.71)	(0.83)	(1.40)	(0.04)	(0.63)	(0.66)
	β_{MKT}	0.93	0.60	-0.33	2.41	1.50	-0.91
		(8.74)	(3.10)	(-1.21)	(8.27)	(6.26)	(-2.62)
	β_{FVIX}	-0.02	-0.29	-0.27	0.98	0.26	-0.71
		(-0.30)	(-1.85)	(-1.23)	(3.97)	(1.37)	(-2.45)

Chapter 2

Option-implied jump risk and the cross-section of stock returns

2.1 Introduction

The option pricing literature provides strong evidence that aggregate jump risk is priced by investors in the options market. In fact, it constitutes nowadays a fundamental premise of state-of-the-art option pricing models.[8] A parallel stream of research examines the impact of jump risk in the time-series variation of equity and variance risk premiums, providing strong evidence that a significant fraction of these two premiums can be ascribed to compensation for jump risk (see Santa-Clara and Yan (2010) and Bollerslev and Todorov (2011)). Despite the importance of jump risk documented in the literature, the investigation of how it affects the cross-section of expected stock returns has received less attention.

The main objective of this chapter is to provide fresh empirical evidence that time-varying jump risk is priced in the cross-section of stock returns. Our theoretical background follows a large body of literature showing how to extract risk-neutral moments from observed option prices (see Bakshi, Kapadia and Madan (2003), among others). As a preliminary step we demonstrate a straightforward relation between the first and second-order moments (in other words, the mean and variance) of the log-return risk-neutral distribution which may be used to approximate the third-order moment of the jump process. As the first two moments can be extracted from option prices, it is straightforward to obtain an approximation of the third-order

[8] The relevant literature is very extensive, including early papers like Bates (1996, 2000) and Pan (2002) up to more recent ones like Ait-Sahalia, Karaman and Mancini (2020).

moment of the jump process from option prices. A similar formula is derived by Du and Kapadia (2012). In addition, we provide theoretical and empirical evidence showing that the third-order moment of the jump process is strongly related to the spot (and expected integrated) variance. Thus, its innovations are affected from both volatility and jump risk. To this end, we suggest a new measure of jump risk exposure by scaling the third-order moment of the jump process with expected integrated variance. Theoretically, this new scaled variable is not related to the dynamics of spot variance, and its innovations can be considered as a proxy of jump risk.

Our empirical approach investigating it aggregate jump risk is priced in the cross-section of stock returns closely follows Ang, Chen, and Xing (2006) and Cremers, Halling, and Weinbaum (2015). Specifically, we estimate jump risk loadings at the individual stock level using daily returns. As a second step, we sort stocks on the realized jump risk loadings, and we investigate whether stocks with higher betas have lower average returns contemporaneously, simultaneously controlling for other risk factors known to affect the cross-section of expected stock returns. We focus on uncovering a contemporaneous relation between jump risk betas and average returns, since it constitutes the essence of a cross-sectional risk-return relation. In addition, we investigate the relation between realized jump-risk betas and future stock returns. By so doing, we examine if realized jump risk exposures predict future ones, allowing us to form investable hedge portfolios ex-ante that have ex-post exposure to jump risk.

Our main result is that jump risk is priced in the cross-section of stock returns, identifying a negative market price of jump risk, consistent with theory. We document that stocks with high jump risk loadings significantly underperform stocks with low ones contemporaneously, producing a statistically and economically significant premium of -9.41% per year at the 1% level. Risk-adjusted returns with respect to the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model are also negative and highly significant. Besides investigating the pricing of aggregate jump risk in the cross-section of stock returns, it is also interesting to decompose jump risk innovations in their upside and downside components and examine the relative contribution of these two in the documented jump risk premium. The results of this exercise clearly show that the negative jump risk premium is due to its downside jump risk component. On the other hand, the premium of the high-low portfolio sorted by upside jump risk betas is not significant.

Our results are robust to bivariate sorts and Fama-MacBeth (1973) regressions. In particular, we show that the negative relation between jump risk betas and contemporaneous raw and risk-adjusted stock returns holds after controlling for volatility and skewness risk exposure. This result is particularly important as preliminary evidence indicate a strong cross-sectional relation between jump risk loadings, and variance or skewness loadings. We also perform Fama-MacBeth (1973) regressions, where we provide evidence for a robust negative relation between the exposure of stocks to aggregate jump risk and contemporaneous stock returns after controlling for several variables suggested in the literature.

Finally, our main results carry over to a predictive setting, in which we compare the subsequent realized monthly returns of the quintile portfolios sorted by jump risk betas estimated over the previous period. We show that the high-low quintile portfolio delivers significant risk-adjusted returns in the following month of the portfolio formation period. These results are robust to different beta estimation windows and return holding periods.

This chapter is closely related to Cremers, Halling, and Weinbaum (2015). They create a jump risk factor from option prices as a delta-neutral, vega-neutral and gamma positive portfolio of straddle positions. This jump risk factor is orthogonal to volatility risk and is negatively priced in the cross-section of stock returns contemporaneously. Our study differs from Cremers, Halling and Weinbaum (2015) in at least two important dimensions. First, we conduct a simulation study to examine the ability of our suggested variable extracted from option prices and the variable constructed by Cremers, Halling, and Weinbaum (2015) to proxy for jump risk. The findings from this exercise are very interesting. While, our jump risk measure, can accurately approximate the third-order moment of the jump size distribution, the jump risk factor of Cremers, Halling, and Weinbaum (2015) fails to proxy for jump risk. The main reason for that is that in practice the straddle portfolio, aiming to acquire exposure to jump risk, is constructed using Black-Scholes sensitivities, which may substantially differ from the true ones. This is especially true for vega. Therefore, the proposed jump risk factor is not actually orthogonal to volatility risk, nor even to market risk. Second, our jump risk loadings can predict the future exposure of stocks to jump risk. Therefore, the results of the contemporaneous cross-sectional analysis carry over to a predictive setting. In Cremers, Halling, and Weinbaum (2015) this is not the case. When stocks are sorted by past jump risk betas, the subsequent average return of the high-low quintile portfolio swings sign from negative to positive.[9] Therefore, an investor who seeks a hedge against jump risk and construct a hedge portfolio ex-ante, will be poorly hedged over the following month. As Barahona, Driessen, and Frehen (2021) show, if betas are unpredictable then investors cannot acquire exposure to a certain risk factor, and thus to create a risk premium. These two observations cast doubt on the jump risk premium identified by Cremers, Halling, and Weinbaum (2015).

Our study is also related to Bollerslev, Li, and Todorov (2016) who estimate jump risk betas from high frequency data. Like us, they find that jump risk is priced in the cross-section of stock returns We complement their results by estimating jump risk betas as the response of stock returns to innovations in the (approximated) third-order moment of the jump size distribution extracted from option prices. In addition, we provide evidence that only downside jump risk is priced in the cross-section of stock returns.

The option pricing literature has long ago related jumps to skewness. Therefore, our study is also related to Chang, Christoffersen, and Jacobs (2009), who investigate the pricing of market skewness risk in the cross-section of stock returns. Our work differs from them in two points. First, in contrast to us, they document a negative market price of skewness risk, which implies a positive jump risk premium which is inconsistent with economic intuition. Second, our jump risk premium remains intact when we control for skewness risk exposure.

Finally, our cross-sectional pricing results also complement recent studies examining the impact of jump risk in the level and time-series variation of equity and variance risk premiums. Santa-Clara and Yan (2010) and Bollerslev and Todorov (2011), among others, provide strong evidence that a large portion of the aggregate equity premium and its time-series variation could be attributable to jump tail risk.

The rest of this chapter is organized as follows. Section 2 sets the theoretical background and discuss how we can approximate a jump risk measure from option

[9] The sign of the high-low quintile portfolio turns out to be negative once more when stocks are sorted by predicted jump risk betas. However, these betas are in-sample predictors (and not out-of-sample) depending on parameter estimates which can be observed ex-post.

prices. Section 3 conducts a small-scaled simulation study to investigate the accuracy of our approach to approximate jump risk. Section 4 describes the data and the methodology used to investigate whether jump risk is priced. Section 5 presents our main results on the pricing of jump risk in the cross-section of stock returns. It also examines the robustness of our results. Section 6 concludes the chapter.

2.2 Theoretical Background

2.2.1 General setup

No-arbitrage implies the existence of a risk-neutral probability measure $\mathbb{Q}$ defined on a probability space $(\Omega, F, \mathbb{Q})$. Let S_t be the stock price at time t. Then, under $\mathbb{Q}$, the stock return can be modeled as a superposition of a predictable drift component and a martingale. The drift component is determined by no-arbitrage. The martingale component can further be decomposed canonically into two orthogonal components: a purely continuous martingale and a purely discontinuous martingale (see Jacob and Shiyaev (1987), p.84). Therefore, S_t solves the following stochastic differential stochastic differential equation:

$$\frac{dS_t}{S_{t-}} = (r-q)dt + \sigma_t dW_t + (exp(J_t) - 1)dN_t - v_t(dx)dt, \tag{2.1}$$

where the instantaneous risk-free rate r and dividend yield q are assumed to be constant, σ_t is the instantaneous volatility process left unspecified and W_t a standard Brownian motion. N_t is a Poisson counting process with stochastic intensity λ_t, J_t is the random price jump size and $v_t = \lambda_t g_t$ is the compensator with $g_t = E_t^{\mathbb{Q}}(exp(J) - 1)$. When a jump occurs at time τ, the induced price change is $(S_\tau - S_{\tau-}) = exp(J_\tau) - 1$, which implies that $log(S_\tau / S_{\tau-}) = J_\tau$. Equation (2.1) models the price change as the sum of a risk-neutral drift and two martingale components: a purely continuous martingale and a purely discontinuous (jump) martingale. This is a very general specification and we do not make any further assumptions about the properties of the jumps or the form of the stochastic volatility process. Indeed, model

(2.1) subsumes virtually all models used in finance with finite jump activity (see Ait-Sahalia, Karaman, and Mancini (2020)).

2.2.2 Jump and tail index implied from option prices

Following Carr and Wu (2009) and Du and Kapadia (2012) we aim to extract a jump risk measure building on the first two (non-central) moments of the stock log-return during the period [*0,T*] and the expected quadratic variation of the log-return process during the same period. The following Proposition states the first important result of our analysis.

Proposition 1 For an asset price process characterized by (2.1) the following result holds:

$$\frac{1}{2}E_0^{\mathbb{Q}}\left[ln(\tfrac{S_T}{S_0})^2\right] = -E_0^{\mathbb{Q}}\left[ln(\tfrac{S_T}{S_0})\right] + (r-q)T + E_0^{\mathbb{Q}}\int_0^T ln(S_{t-}/S_0)dlnS_t + J_0(T), \quad (2.2)$$

where

$$J_0(T) = E_0^{\mathbb{Q}}\int_0^T \psi(J_t)dN_t, \quad (2.3)$$

with $\psi(x) = (1 + x + x^2/2) - e^x$.

Proof. In order to demonstrate this Proposition, we first apply Itô's lemma to model (2.1) to retrieve to log of the stock price as:

$$ln\left(\frac{S_T}{S_0}\right) = \int_0^T \frac{dS_t}{S_{t-}} - \frac{1}{2}\int_0^T \sigma_t^2 dt + \int_0^T (1 + J_t - e^{J_t})dN_t. \quad (2.4)$$

Then define the quadratic variation of the log of the stock price process over the period [*0,T*] as:

$$[ln\,S, ln\,S]_{0,T} = \int_0^T \sigma_t^2 dt + \int_0^T {J_t}^2 dN_t. \quad (2.5)$$

Combining (2.4) and (2.5) yields:

$$ln\left(\frac{S_T}{S_0}\right) = \int_0^T \frac{dS_t}{S_{t-}} - [\ln S\,, \ln S]_{0,T} + \int_0^T \psi(J_t)dN_t. \quad (2.6)$$

We then apply Itô's lemma to retrieve the squared of the log of the stock price as:

$$ln(\frac{S_T}{S_0})^2 = 2\int_0^T ln(S_{t-}/S_0)dlnS_t + [ln\,S, ln\,S]_{0,T}. \tag{2.7}$$

Substituting equation (2.7) into (2.6), taking conditional expectations under measure $\mathbb{Q}$, and rearranging terms yields formula (2.2). ■

This result relates (through the expected quadratic variation) the first and second-order (non-central) moments of the log-return distribution with term $J_0(T)$ that depends on the stock price discontinuous component. Intuitively, as $\psi(x) \approx -x^3/3!$, $J_0(T)$ captures the (opposite of the) third-order moment of the jump measure.

Furthermore, it is well-known in the literature that the moments of the log-return distribution under measure $\mathbb{Q}$ can be directly obtained from a portfolio of European out-of-the money (OTM) call and put options (see Bakshi, Kapadia, and Madan (2003) and Rompolis and Tzavalis (2017)). Therefore, our second Proposition shows how term $J_0(T)$ can be proxied by a portfolio of European call and put options.

Proposition 2 For an asset price process characterized by (2.1) the following result holds:

$$J_0(T) = e^{rT}\left[\int_{S_0}^{\infty}\frac{\ln\left(\frac{S_0}{K}\right)}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{\ln\left(\frac{S_0}{K}\right)}{K^2}P_0(K,T)dK\right] + A_0(T), \tag{2.8}$$

where

$$A_0(T) = \left(e^{(r-q)T} - (r-q)T - 1\right) - E_0^{\mathbb{Q}}\int_0^T \ln\left(\frac{S_{t-}}{S_0}\right)dlnS_t, \tag{2.9}$$

and $C_0(K,T)$ ($P_0(K,T)$) denotes the price of a European call (put) option observed at time 0 with strike price K and time-to-maturity T.

Proof. Bakshi, Kapadia, and Madan (2003) show that:

$$E_0^{\mathbb{Q}}\left[ln(\frac{S_T}{S_0})^2\right] = 2e^{rT}\left[\int_{S_0}^{\infty}\frac{1}{K^2}\left(1-\ln\left(\frac{K}{S_0}\right)\right)C_0(K,T)dK \right.$$
$$\left. + \int_0^{S_0}\frac{1}{K^2}\left(1-\ln\left(\frac{K}{S_0}\right)\right)P_0(K,T)dK\right]. \tag{2.10}$$

Rompolis and Tzavalis (2017) further demonstrate that:

$$E_0^{\mathbb{Q}}\left[ln\left(\frac{S_T}{S_0}\right)\right] = E_0^{\mathbb{Q}}\left[\frac{S_T}{S_0}\right] - 1$$
$$- e^{rT}\left[\int_{S_0}^{\infty}\frac{1}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{1}{K^2}P_0(K,T)dK\right]. \tag{2.11}$$

Substituting equations (2.10) and (2.11) into (2.2) and rearranging terms yields formula (2.7). ■

Formula (2.7) is also demonstrated by Du and Kapadia (2012) in a slightly different fashion. The results of Proposition 2 indicate that $J_0(T)$ can be calculated as the sum of a portfolio of OTM call and put options and the term $A_0(T)$. The portfolio consists of long positions in OTM puts and short positions in OTM calls. Intuitively, as the prices of OTM calls (puts) increase due to the expectation of a future upside (downside) jump, $J_0(T)$ decreases (increases) indicating an increase (decrease) in the third-order moment of the jump measure.

As long as $A_0(T)$ is negligeable, $J_0(T)$ can be accurately approximated by the portfolio of OTM options. Indeed, Du and Kapadia (2012) impose some mild additional assumptions on model (2.1) and show that $A_0(T) = O(T^2)$. Therefore, for a short maturity period T, the impact of $A_0(T)$ can be neglected, so that,

$$J_0(T) \approx e^{rT}\left[\int_{S_0}^{\infty}\frac{ln(S_0/K)}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{ln(S_0/K)}{K^2}P_0(K,T)dK\right]. \tag{2.12}$$

Formula (2.12) enables us to retrieve $J_0(T)$ without imposing any parametric structure in our model using the observed prices of European call and put options.

2.2.3 A new scaled measure of upside and downside jump risk

As noted previously, function $\psi(x) \approx -x^3/3!$, so that $J_0(T)$ approximates the (opposite) of the third-order moment of the jump measure under measure $\mathbb{Q}$, i.e.,

$$J_0(T) \approx -\frac{1}{3!} E_0^{\mathbb{Q}} \int_0^T J_t^3 dN_t. \tag{2.13}$$

To better grasp the nature of $J_0(T)$ and the factors underlying its dynamics, we need to put more structure in the model. To this end, we assume that jump arrivals intensity is stochastic and depends on the spot variance, i.e., $\lambda_t = \lambda\sigma_t^2$ where $\lambda > 0$ (see Andersen, Fusari and Todorov (2017)). The assumption regarding the temporal variation of jump intensity related to spot variance is followed by a broad number of relevant studies (see, e.g., Pan (2002), Ait-Sahalia, Karaman, and Mancini (2020)). Moreover, we assume the distribution of J_t is time-invariant. Under these assumptions $J_0(T)$ can be written as:

$$J_0(T) \approx -\frac{1}{3!} \lambda E_0^{\mathbb{Q}}(J^3) E_0^{\mathbb{Q}} \int_0^T \sigma_t^2 dt. \tag{2.14}$$

Let $\mu_{(3)}^J = E_0^{\mathbb{Q}}(J^3)$ denote the third-order moment of the jump size distribution and $EIV_0(T) = E_0^{\mathbb{Q}} \int_0^T \sigma_t^2 dt$ is the expected integrated variance. Then,

$$J_0(T) \approx -\frac{1}{3!} \lambda \mu_{(3)}^J EIV_0(T). \tag{2.15}$$

The last relationship implies that $J_0(T)$ is the product of the third-order moment of the jump size distribution and the expected integrated variance. Thus,

$$\frac{J_0(T)}{EIV_0(T)} \approx \frac{1}{3!} \lambda \mu_{(3)}^J. \tag{2.16}$$

Hence, if we scale $J_0(T)$ with $EIV_0(T)$ we obtain a measure of the third-order moment of the jump size distribution.

In order to be able to apply formula (2.16) in practice, we need to scale $J_0(T)$, approximated by a portfolio of OTM call and put options as equation (2.12) indicates, with an estimate of $EIV_0(T)$. This estimate is provided in the next Proposition.

Proposition 3 For an asset price process characterized by (2.1) the following result holds:

$$EIV_0(T) = 2e^{rT}\left[\int_{S_0}^{\infty}\frac{1}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{1}{K^2}P_0(K,T)dK\right] + B_0(T), \quad (2.17)$$

with

$$B_0(T) = 2\left(1 + (r-q)T - e^{(r-q)T}\right) + 2\int_0^T (1 + J_t - e^{J_t})dN_t. \quad (2.18)$$

Proof. The proof uses several results already found in the two previous demonstrations. In particular, formula (2.4) implies that:

$$\frac{1}{2}EIV_0(T) = -E_0^{\mathbb{Q}}\left[ln\left(\frac{S_T}{S_0}\right)\right] + (r-q)T + \int_0^T (1 + J_t - e^{J_t})dN_t. \quad (2.19)$$

Importing equation (2.11) in the previous formula yields:

$$EIV_0(T) = 2e^{rT}\left[\int_{S_0}^{\infty}\frac{1}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{1}{K^2}P_0(K,T)dK\right] + B_0(T), \quad (2.20)$$

with

$$B_0(T) = 2\left(1 + (r-q)T - e^{(r-q)T}\right) + 2\int_0^T (1 + J_t - e^{J_t})dN_t. \quad (2.21)$$

■

This Proposition indicates that $EIV_0(T)$ can be approximated by a portfolio of OTM call and put options assuming that the effect of the jump term $B_0(T)$ is negligeable. In other words,

$$EIV_0(T) = 2e^{rT}\left[\int_{S_0}^{\infty}\frac{1}{K^2}C_0(K,T)dK + \int_0^{S_0}\frac{1}{K^2}P_0(K,T)dK\right]. \quad (2.22)$$

Note here that the VIX index follows directly from this analysis.

2.3 Simulation study

In this section we conduct a small-scaled simulation study. The aim of it is twofold. First, we examine the accuracy of the option-implied scaled jump risk measure to approximate the third-order moment of the jump size distribution. Second, we measure the performance of the delta-neutral, vega-neutral and gamma positive strategy suggested by Cremers, Halling, and Weinbaum (2015) to proxy for jump risk. We assume that stock prices are generated by the stochastic volatility with random jumps model with state-dependent stochastic intensity process (see Bates (2000) and Pan (2002)). In particular, we assume the following data-generating process, under risk-neutral measure $\mathbb{Q}$, for the stock price S

$$\frac{dS_t}{S_{t-}} = (r - q - \mu\lambda\sigma_t^2)dt + \sigma_t dW_t^S + (exp(J_t) - 1)dN_t \qquad (2.23)$$

$$d\sigma_t^2 = \kappa(\theta - \sigma_t^2)dt + \eta\sigma_t dW_t^\sigma,$$

where W_t^S and W_t^σ are two standard Brownian motions with correlation coefficient ρ, J_t is the random jump size conditional on a jump occurring, with time-invariant normal distribution $J_t \sim N(\mu_J, \sigma_J^2)$ and a mean relative jump size $\mu = exp(\mu_J + \frac{1}{2}\sigma_J^2) - 1$. N_t is the Poisson counter with a state-dependent stochastic intensity process $\lambda\sigma_t^2$ for some $\lambda > 0$. The assumption of a stochastic intensity process which is affine on the latent spot variance is in accordance with our previous theoretical discussion in Section 2.2.3.

We conduct our experiments by simulating model (2.23) using the parameters estimated by Pan (2002) at a daily frequency for a 1-year period.[10] At each day of our sample period we calculate the theoretical European call and put prices with 1 and 2-month time-to-maturity for a moneyness level of [0.75,1.25]. Using the 1-month time-to-maturity theoretical option prices we approximate $J_0(T)$ using formula (2.12) and

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[10] These parameters are equal to: $\kappa = 3.3, \theta = 0.03, \eta = 0.3, \rho = -0.53, \lambda = 12.3, \mu_J = -0{,}21, \sigma_J = 0.038$. We also assume that $r = 0.05$ and $q = 0.0015$. The initial values of the stock price and spot variance are set to $S_0 = 100$ and $\sigma_0 = 0.015$, respectively.

$J_0(T)/EIV_0(T)$, where $EIV_0(T)$ is approximated by formula (2.22).[11] We compare the values of the option-implied $J_0(T)$ and $J_0(T)/EIV_0(T)$ to the third-order moment of the jump process (see equation (2.15)) and the third-order moment scaled by the continuous part of the expected quadratic variation, respectively. Model (2.23) implies that the third-order moment of the jump process is equal to $-\frac{1}{3!}\mu^J_{(3)}F(T,\sigma_0)$, where $\mu^J_{(3)}$ is the time-invariant third-order moment of J_t and

$$E_0^{\mathbb{Q}}\int_0^T \sigma_t^2 dt = F(T,\sigma_0) = T(m(T)\sigma_0 + (1-m(T))\theta), \tag{2.24}$$

where $m(T) = \frac{1-e^{-\kappa T}}{\kappa T}$. Clearly, the third-order moment scaled by the continuous part of the expected quadratic variation is equal to $-\frac{1}{3!}\mu^J_{(3)}$.

The results of the first exercise are presented in Table 1, Panel A. Figure 1 presents the time-series theoretical and approximated values of $J_0(T)$ and $EIV_0(T)$. The results of the table and the graphs of Figure 1 clearly indicate that the option-implied $J_0(T)$ can very accurately approximate the third-order moment of the jump process. The root mean square error (RMSE) is virtually zero while the mean percentage error (MPE) is close to 6%. The results of the table also show that the approximation error increases when we calculate $J_0(T)/EIV_0(T)$. This is due to the error encountered in the approximation of $EIV_0(T)$ by formula (2.22) as the graphs of Figure 1 also indicate. Still, the RMSE is equal to 0.0067 and the MPE is close to 30%.

The second experiment examines the performance of the delta-neutral, vega-neutral and gamma positive strategy suggested by Cremers, Halling, and Weinbaum (2015) as a proxy of a jump risk factor. We use at-the-money (ATM) options with 1 and 2-month time-to-maturity to form delta-neutral straddle positions. We then form a jump risk factor mimicking portfolio (denoted as JUMP) by taking one long position in 1-month straddle and $vega_{1M}/vega_{2M}$ short positions in the 2-months straddle. $vega_{1M}$ ($vega_{2M}$) denotes the vega of the 1-month (2-months) straddle position. Following Cremers, Halling, and Weinbaum (2015), option sensitivities are

[11] Since these formulas employ integrals of continuous functions to obtain $J_0(T)$ and $EIV_0(T)$ based on them, we can employ cubic splines to interpolate the implied by our option prices volatilities between two different points of the data. Due to the lack of option prices at zero and ∞ we extrapolate the implied volatilities over the intervals $(0, K_{min}]$ and $[K_{max}, \infty)$, where K_{min} and K_{max} are the minimum and maximum strike prices from our data, respectively. Our results are based on a constant extrapolation scheme, as common in the literature, that is, assuming that the implied volatility function is flat outside the observed strike price interval.

approximated using the Black-Scholes model and the implied volatility of the respective options. We compare the approximated JUMP factor of Cremers, Halling, and Weinbaum (2015) with the theoretical one calculated using option sensitivities derived by model (2.23).

The results of this second exercise are presented in Table 1, Panel B. We report the mean and standard deviation of the approximated and true JUMP risk factor along with the RMSE and MPE. The average negative value of the true JUMP risk factor is consistent with a negative jump risk premium that this strategy is exposed. In contrast, the approximated one has a positive mean value, large variability, and deviates substantially, from the true one, as the RMSE and MPE metrics indicate. In fact, they have a large negative correlation of -87%. Therefore, the approximated JUMP risk factor suggested by Cremers, Halling, and Weinbaum (2015) cannot be considered as a robust proxy of jump risk premium as this counterexample shows. Why this happens? The reason is that the Black-Scholes option sensitivities (and especially vega) are poor proxies of the true ones. This is clearly observed in Figure 2, which plots call option delta, vega and gamma across moneyness levels for one indicative day of our sample. The direct implication of this misspecification error is that the approximated JUMP risk factor is not a delta-neutral and vega-neutral strategy. In fact, the average delta of the strategy is equal to 0.33, while the average vega is equal to 8.58, indicating that the approximated JUMP risk factor is also exposed to market and volatility risk.

2.4 Data, Variables and Empirical Methodology

This section describes our data and the empirical methodology we use to extract the jump risk measure from observed option prices. It also presents the empirical design we employ to investigate the pricing of jump risk in the cross-section of stock returns.

2.4.1 Data

For the empirical analysis, we obtain data from various sources. We get returns, market capitalization and prices for all ordinary common shares (share code 10 and 11) from the CRSP database. Option data for the S&P 500 index are downloaded from OptionMetrics for the period January 1996 to April 2016, we use standardized option data from the surface file in order to obtain a constant maturity for our options every day. Accounting data are obtained from Compustat. The returns on the market premium, SMB, HML and MOM factors are obtained from Kenneth French's online data library.[12]

2.4.2 Extracting the jump risk measure from observed option prices

This part of the chapter shows how to calculate $J_0(T)$ and $EIV_0(T)$ using equations (2.12) and (2.22), respectively, from observed option prices. The estimates of these two variables will then be used to calculate a scaled measure of jump risk according to equation (2.16). Furthermore, for the purpose of our analysis we calculate the option-implied variance and skewness (denoted as VAR and $SKEW$ henceforth) of the S&P 500 index return using Bakshi, Kapadia, and Madan (2003) formula (see Appendix B for details).

We calculate the option-implied jump risk measure $J_0(T)$ and expected integrated variance $EIV_0(T)$ of the S&P500 index at a daily frequency following Du and Kapadia (2012) and Bakshi, Kapadia, and Madan (2003) using 30-day constant maturity options from the implied volatility surface file. More specifically, every day we interpolate implied volatilities between the lowest and highest available moneyness using cubic splines and perform constant extrapolation with 1% and 300% as bounds. Subsequently, we convert implied volatilities to option prices using the Black-Scholes formula, where moneyness levels less than 1 are used to create OTM put prices and moneyness levels more than 1 are used to create OTM call prices

[12] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

which are used to calculate $J_0(T)$ and $EIV_0(T)$. For the rest of the chapter, $J_0(T)$ which is computed using this approach with $T = 30$ days is denoted as JTI. The scaled measure of jump risk, which is denoted as $JTIsc$, is derived by dividing $J_0(T)$ with $EIV_0(T)$ following the analysis of Section 2.2.3.

In addition, we decompose $J_0(T)$ into a downside jump risk measure $J_0^{(-)}(T)$ and an upside jump risk measure $J_0^{(+)}(T)$ following Du and Kapadia (2012). The downside jump risk measure corresponds to the OTM put portfolio, while the upside jump risk measure corresponds to the OTM call portfolio.[13] This decomposition is further supported by the analysis of Bollerslev and Todorov (2011) that demonstrate that the prices of short-maturity OTM options are dominated by the jump measure. Intuitively, over short time intervals, changes in the price due to the continuous component are invariably small relative to the possible impact of large jumps, and the diffusive part may be ignored. Moreover, they show that if the jump measure is separated in an upside and downside jump term, then OTM call prices depend on the upside jump component, while OTM put prices depend on the downside jump component. Following the previous analysis, we also scale $J_0^{(-)}(T)$ and the opposite of $J_0^{(+)}(T)$ by dividing them with $EIV_0(T)$. For the rest of the chapter, we denote $J_0^{(-)}(T)$ and the inverse of $J_0^{(+)}(T)$, which are computed from S&P500 index option data using the aforementioned empirical approach with $T = 30$ days, as $JTIN$ and $JTIP$, respectively. The scaled measure of downside and upside jump risk is denoted as $JTINsc$ and $JTIPsc$, respectively.

To derive the innovations in JTI, $JTIP$ and $JTIN$ and their respective scaled measures we use the daily changes in each variable as in Ang, Hodrick, Xing and Zhang (2006) and Agarwal, Bakshi and Huij (2009).

[13] Technically, we define $J_0^{(-)}(T)$ and $J_0^{(+)}(T)$ as:

$$J_0^{(-)}(T) = e^{rT} \int_0^{S_0} \frac{\ln(S_0/K)}{K^2} P_0(K,T)dK,$$

and

$$J_0^{(+)}(T) = e^{rT} \int_{S_0}^{+\infty} \frac{\ln(S_0/K)}{K^2} C_0(K,T)dK,$$

respectively.

Finally, we calculate 30-day constant maturity estimates of VAR and $SKEW$ of the S&P500 index at a daily frequency using once more the aforementioned numerical approach. VAR and $SKEW$ innovations are calculated as daily changes in each variable.

2.4.3 Empirical methodology

Our research design follows closely Ang, Chen and Xing (2006) and Cremers, Halling and Weinbaum (2015) in considering the contemporaneous relation between the realized factor loadings and realized stock returns. The contemporaneous relation between factor loadings and risk premium is the essence of the risk-return relation.

Our empirical methodology employs portfolio sorts, in which stocks are sorted on their individual factor loading estimated over a given time period. Realized average returns are also computed over the same time period, enabling us to examine the contemporaneous risk-return relation.

In particular, for each stock i we estimate betas using daily returns over rolling annual periods every month from the following regression:

$$r_t^i = \beta_0^i + \beta_{MKT_t}^i MKT_t + \beta_{MKT_{t-1}}^i MKT_{t-1} + \beta_{\Delta X_t}^i \Delta X_t + \beta_{\Delta X_{t-1}}^i \Delta X_{t-1} + \varepsilon_t^i \tag{2.25}$$

where r_t^i is the excess return of stock i on day t, MKT_t is the market premium (the excess return of the market portfolio proxied by the CRSP value-weighted index) on day t, and ΔX_t is the daily innovation in the variable of interest. We also include one-day lagged risk factors (see Dimson (1979)) and use the sum of the betas for each risk factor as in Cremers, Halling, and Weinbaum (2015) to mitigate the impact of infrequent trading. Following Bali, Engle, and Murray (2016) we require at least 200 non-missing observations in order to estimate the betas. Other factors may also influence the returns of individual stocks. We do not include these factors in regression (2.25) as they might add noise in the estimation of $\beta_{\Delta X_t}^i$. We do, however, control for a number of them when conducting the cross-sectional asset pricing tests.

Following the relevant literature (see, e.g., Ang, Chen, and Xing (2006)), at the beginning of each month, we sort stocks into quintiles based on their $\beta^{i}_{\Delta X_t}$ loadings estimated from equation (2.25) over the previous 12 months. We then compute the average portfolio excess returns over the same 12 months used to estimate the factor loadings. To ensure that our results are robust to other factors known to affect stock returns, we estimate portfolio alphas using the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model.

We conduct a number of robustness checks to ensure that our results are not driven by other risk factors. First, we perform dependent bivariate sorts to show that jump risk is priced in the cross-section of stock returns when controlling for the exposure of stocks on VAR and $SKEW$ innovations. Second, we perform Fama-MacBeth (1973) regressions that allows us to simultaneously control for more than one stock characteristics. Finally, we extend our empirical methodology to a predictive setting. Although, the contemporaneous relation between returns and factor risk loadings represents the essence of the risk-return relation, is not of much practical value if the betas cannot be used to predict future returns. In so doing, we sort stocks into quintiles based on the realized betas over the past 12 months, and then compute average returns and alphas over the following month.

2.5 Empirical Results

This section describes our main empirical results on the pricing of jump risk in the cross-section of stock returns. We first, present summary statistics of jump risk measures extracted from option prices. Secondly, we present summary statistics of the factor loadings on jump risk. We then discuss the results of portfolio sorts. Finally, we consider various robustness checks to ensure that our results are not driven by the exposure of stocks to other risk factors.

2.5.1 Summary statistics of jump risk measures

We begin our empirical investigation by examining the properties of jump risk measures and their innovations extracted from traded option prices. Table 2 presents descriptive statistics of selected variables (Panel A) and the time-series correlations of their innovations (Panel B). The average value of JTI is positive corresponding to a negative skewed jump size distribution. Furthermore, as the 5% percentile indicates, JTI is positive for almost all data points exhibiting positive skewness and positive excess kurtosis. The results of the table also indicate that the bulk of JTI variation is due to $JTIN$. The approximately 3 times higher mean value of the downside jump risk measure, $JTIN$, compared to the upside jump risk one indicates that OTM put options are more expensive than OTM call options. This is consistent with the smirk pattern observed in the S&P 500 index implied volatility curves, termed as crash-o-phobia by Rubinstein (1994) which is also present in other major equity indices (see Foresi and Wu (2005)). Moreover, $JTIN$ has twice the variability of $JTIP$. Similar conclusions can be drawn by inspecting the descriptive statistics of the scaled measures of jump risk. The statistically significant average positive value of $JTIsc$, equal to 0.0185, indicates that the jump size distribution is negatively skewed. Again, the bulk of its variation is due to the downside jump risk component. $JTINsc$ exhibits an approximately 3 times higher mean value and standard deviation compared to $JTIPsc$.

The results of Panel B indicate that innovations in the jump risk measures are positively correlated with innovations in variance. For example, the correlation coefficient between ΔJTI and ΔVAR is 60%. This is consistent with our theoretical framework, indicating that random jump intensity is related to spot variance. Jump innovations have a 95% and 51% correlation with downside and upside jump innovations, respectively, indicating that shifts in JTI are mainly due to downside jump innovations. Moreover, downside and upside jump innovations show a positive correlation coefficient of 73%. In contrast, variance-scaled downside and upside jump innovations show a negative correlation of -27%, indicating that the positive correlation of the unscaled variables is due to their relation to variance. Moreover, both variance-scaled upside and downside jump innovations have the expected sign on the correlation coefficient with $\Delta SKEW$. A positive (negative) downside (upside) jump innovation is related to a decrease (increase) in skewness. Interestingly, $\Delta JTIsc$ exhibits a negative correlation with excess markets returns of -52%, while correlations with other factors are much lower in absolute magnitude. Finally, note that the variance-scaled jump risk measures innovations have a positive correlation with ΔVAR which is lower in magnitude compared to the correlation of the unscaled variables.

Figure 3 plots monthly innovations in the scaled jump risk measures for our sample period (January 1996-April 2016). The highest innovation in all three variables is observed in the aftermath of Lehman Brothers default in October 2008. Additional significant spikes occur during the Asian currency crisis in 1997 and the LTCM default in 1998. The plots of the figure also confirm the high correlation between innovations in $JTIsc$ and $JTINsc$.

2.5.2 Summary statistics of estimated betas

Our main empirical results are based on betas on jump innovations estimated for individual stocks in the sample. For each stock we estimate betas with respect to $\Delta JTIsc$, $\Delta JTINsc$, and $\Delta JTIPsc$, using daily returns over rolling annual periods every month from regression (2.25). In Table 3 we present summary statistics of these factor loadings where we also include betas on ΔVAR and $\Delta SKEW$. Betas on $\Delta JTIsc$, $\Delta JTINsc$, and $\Delta JTIPsc$ have positive mean and median, exhibit positive skewness and are leptokurtic, indicating that although most stocks have returns that are positively related to jump risk measure innovations, a group of them are inversely related. Panel B shows the time-series average of cross-sectional correlations of betas. Betas on scaled jump risk measures are positively correlated with variance betas and downside (upside) scaled jump shows a negative (positive) correlation coefficient of -69% (89%) with skewness betas as expected. Panel C presents monthly autocorrelations of betas. We observe high autocorrelation coefficients in the first lags which is justified from the use of overlapping annual windows in the beta estimation regression. The figure also indicates that after lag 6 the autocorrelation of all betas decreases significantly and becomes insignificant after lag 12. These results have straightforward implications for the predictive regressions that we examine later, indicating that past betas can predict future betas at least in the medium-term.

To visualize the time-series and cross-sectional variation in the betas on our main variables of interest, i.e., $\Delta JTIsc$, $\Delta JTINsc$, and $\Delta JTIPsc$, Figure 4 shows the time-series of value-weighted portfolio betas, based on monthly quintile sorts. We observe a higher dispersion among $\beta_{\Delta JTIsc}$ and $\beta_{\Delta JTINsc}$ compared to $\beta_{\Delta JTIPsc}$. It is also evident that higher dispersion among betas is detected during periods of market stress, like for example, 2000-2002 and 2008-2010. This excess dispersion is mainly due to the increase of the stock's betas in the high quintile portfolio, indicating that during periods of market stress the positive relation between $\Delta JTIsc$ and high beta stock returns further increases.

2.5.3 Univariate portfolio sorts

This section presents the main empirical results of the chapter. It investigates whether jump risk is priced in the cross-section of stock returns through portfolio sorts. Every month we create value-weighted portfolios by sorting stocks into quintiles based on the jump risk betas estimated over the previous 12-month period. We compute average realized excess returns and portfolio characteristics over the same 12 months.

Table 4, Panel A, presents the results for contemporaneous value-weighted quintile portfolios sorted by $\beta_{\Delta JTIsc}$. Several conclusions can be drawn from these results. First, as Panel A indicates stocks with a higher exposure to aggregate jump risk (i.e., low beta) measured by $\Delta JTIsc$ earn higher returns. In fact, the low quintile portfolio average return is equal to 13.22% per year. The relation between quintile portfolio beta and average return shows a decreasing monotonic pattern, leading to a high quintile portfolio with an average return of 3.81%. Therefore, the high-low quintile portfolio sorted by $\beta_{\Delta JTIsc}$ produces a strongly statistically and economically significant premium of -9.41% per year. This is consistent with a negative market price of aggregate jump risk. Stocks with low sensitivities to jump risk are exposed to aggregate jump risk and earn high returns. In contrast, stocks with high sensitivities to jump risk hedge against jump risk and investors are willing to accept a lower return for them. Second, the negative premium of the high-low portfolio is robust to other known risk factors. Risk-adjusted returns with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model are very close to the documented average return and both are statistically significant at 1% level. Third, even though the relation between betas and portfolio average returns is monotonic, the bulk of the spread between the high and low quintile portfolios comes from the spread between the fourth and highest quintile. This result suggests that it is the underperformance of stocks that hedge against aggregate jump risk that is largely responsible for the negative premium of the high-low quintile portfolio. Fourth, consistent with the correlation coefficients between betas reported in Table 3, we observe a monotonic pattern in $\beta_{\Delta JTINsc}$, $\beta_{\Delta JTIPsc}$, $\beta_{\Delta VAR}$ and $\beta_{\Delta SKEW}$, of the quintile portfolios sorted by $\beta_{\Delta JTIsc}$. In fact, high (low) $\beta_{\Delta JTIsc}$ stocks have high (low) $\beta_{\Delta JTINsc}$ and low (high) $\beta_{\Delta JTIPsc}$. Thus, stocks hedging against aggregate jump risk, hedge against downside jump risk, while they are exposed to upside jump risk. Moreover, high (low) $\beta_{\Delta JTIsc}$ stocks have high (low) $\beta_{\Delta VAR}$ and low (high) $\beta_{\Delta SKEW}$, indicating that stocks hedging against jump risk can also hedge against aggregate volatility risk, while they are exposed to skewness risk. Fifth, the high-low quintile portfolio sorted by $\beta_{\Delta JTIsc}$ is also exposed to market risk, indicating that high beta stocks hedge against jump risk. Finally, the spread portfolio has a negative exposure on the HML factor. Thus, stocks which are exposed on aggregate jump risk (low $\beta_{\Delta JTIsc}$) are also exposed to the value factor. Therefore jump risk can help in explaining defensive and value anomalies.

Besides investigating the pricing of aggregate jump risk in the cross-section of stock returns, it is also interesting to decompose jump innovations in their upside and downside components and examine the relative contribution of these two in the documented jump risk premium. The results of this exercise are shown in Table 4, Panel B and C. These results clearly show that the negative jump risk premium is due to its downside jump risk component. On the contrary, the high-low quintile portfolio based on $\beta_{\Delta JTIPsc}$ fails to deliver a significant premium in raw or risk-adjusted basis. Therefore, in the reminder of the chapter we focus our investigation on the pricing of downside aggregate jump risk.

2.5.4 Bivariate portfolio sorts

The results of the previous section reveal that stocks which are exposed to jump risk, they are also exposed to volatility and skewness risk. Therefore, one may argue that the documented premium reflects the exposure of stocks on aggregate volatility risk (see Ang, Hodrick, Xing and Zhang (2006)) and/or skewness risk (see Chang, Christoffersen and Jacobs (2009)). To examine this issue in depth we perform dependent bivariate sorts to examine if the spread portfolio still produces significant premium when controlling for $\beta_{\Delta VAR}$ and $\beta_{\Delta SKEW}$. More specifically, we first sort stocks based on $\beta_{\Delta VAR}$ or $\beta_{\Delta SKEW}$ in quintiles, then within each quintile we further sort stocks on $\beta_{\Delta JTINsc}$, resulting in a total of 25 portfolios.

Table 5 reports the results. The high-low quintile portfolio sorted by $\beta_{\Delta JTINs}$ provides significant average returns and alphas when controlling for $\beta_{\Delta VAR}$ (see Panel A). Not surprisingly, the average return is reduced to -3.83% per year but remains statistically significant at the 5% level. The results of the table also indicate that this negative premium is mainly due to stocks in the highest $\beta_{\Delta VAR}$ quintile. Therefore, the highest variation in the cross-section of stock returns due to their exposure to downside jump risk is observed for stocks that hedge against aggregate volatility risk. In addition to that, we observe that the highest $\beta_{\Delta VAR}$ and $\beta_{\Delta JTINsc}$ portfolio which hedges against both aggregate volatility and downside jump risk provides the lowest return across all 25 portfolios of -1.21% per year.

Furthermore, the significant negative premium of the high-low portfolio sorted by $\beta_{\Delta JTINsc}$ is robust when controlling for $\beta_{\Delta SKEW}$ (see Panel B). The average return of the high-low quintile portfolio is -8.6% per year and statistically significant at the 1% level. Moreover, average return and alphas of the spread portfolio remain negative and significant across almost all $\beta_{\Delta SKEW}$ quintiles. Interestingly though, the lowest value is observed in the low $\beta_{\Delta SKEW}$ quintile, indicating that the highest variation in the cross-section of stock returns due to their exposure to downside jump risk is observed for stocks that hedge against aggregate skewness risk.

The conclusion drawn by the section is that, although jump risk measure innovations are correlated to innovations in variance and skewness as shown in Table 3, the documented negative premium of the high-low portfolio sorted by jump risk betas cannot be explained by the exposure of stocks to volatility or skewness risk.

2.5.5 Fama-MacBeth regressions

The portfolio sorts provide strong evidence that jump risk exposure are related to contemporaneous average stock returns. In addition, the sign of the average return of the high-low portfolio further suggests negative price of risk for aggregate jump innovations, consistent with asset pricing theory. However, they ignore the potential effect of other explanatory variables known to explain the cross-sectional variation of stock returns. Furthermore, aggregating the stocks into quintile portfolios may ignore potentially important cross-sectional firm-level information. To address these issues, we perform Fama-MacBeth (1973) multivariate regressions, conducted at the firm level, that allows us to simultaneously control for more than one stock characteristics. These include market capitalization, book-to-market ratio, momentum, mispricing, idiosyncratic volatility, and illiquidity. The definition of each variable is provided in Appendix A.

Table 6 presents the time-series averages of cross-sectional coefficients alongside with the Newey-West (1987) t-statistics. We show that the $\beta_{\Delta JTINsc}$ coefficient is negative and statistically significant while controlling for the market capitalization, book-to-market, momentum, mispricing, idiosyncratic volatility, and illiquidity. This result confirms that jump risk is priced in the cross-section of stock returns and price of jump risk is negative. The effect is also economically significant. A two-standard deviation (equal to 2.30) increase across stocks in $\beta_{\Delta JTINsc}$ together with the estimated premium of -0.012 from specification (6), is associated with a 5.52% drop in expected return per year.

Overall, the evidence presented so far suggests that jump risk is priced in the cross-section of stock returns. Systematic jump exposure matters for stocks expected returns. These results are in line with previous studies examining the pricing of jump risk in the cross-section of stock returns (see Cremers, Halling and Weinbaum (2015) and Bollerslev, Li and Todorov (2017)). They also complement the empirical findings of previous studies examining jump risk premium, in the market level, using time-series stock and options data (see, e.g., Santa-Clara and Yan (2010), Bollerslev and Todorov (2011)).

2.5.6 Predictive single-sorted portfolios

The results reported so far focus on the contemporaneous relation between jump risk betas and stock returns. While we find strong evidence that jump risk is priced in the cross-section of stock returns, these results have limited practical value as they cannot be used to form an ex-ante investment strategy that can be followed to construct hedge portfolios. Furthermore, as Barahona, Driessen and Frehen (2021) show, if betas are unpredictable then investors cannot acquire exposure to a certain risk factor, and thus to create a risk premium. They suggest that cross-sectional asset pricing tests should employ betas that are observable to investors rather than using realized betas that are only observable ex-post. In this section, we extent the previous analysis forming predictive single-sorted portfolios.

As previously, we estimate the different betas over the past 12 months. We then sort stocks according to each of different betas and compute the returns the following month. We report average excess returns and risk-adjusted returns in annual basis with respect to the Fama and French (1993) 3-factor model and Carhart (1997) 4-factor model.

Table 7 summarizes the results. As Panel A indicates, we continue to see a monotonically decreasing relation between the future portfolio returns and past $\beta_{\Delta JTIsc}$. Consistent with the slowly decaying autocorrelations for $\beta_{\Delta JTIsc}$ shown in Table 3, the high-low portfolio average return, equal to -4.2% per year, remains negative though lower in magnitude, and statistically insignificant, compared to the contemporaneous average return reported in Table 4. However, it delivers negative and statistically significant risk-adjusted returns with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-model at the 10% level. In addition, the estimated alphas are close in magnitude to those reported in the contemporaneous setting. These results suggest that past jump risk betas are able to predict the cross-sectional variation in the future stock returns. Furthermore, the relation between $\beta_{\Delta JTIsc}$ and future stock returns cannot be explained by the size, book-to-market and momentum factors. As previously, we decompose jump risk in its downside and upside component and estimate downside ($\beta_{\Delta JTINsc}$) and upside $\beta_{\Delta JTIPsc}$) jump risk betas. Consistent with the previous empirical findings, we see that the documented negative jump risk premium is due to its downside jump risk component. Once more, upside jump risk is not priced in the cross-section of stock returns.

2.5.7 Beta estimation and return holding periods

The predictive portfolio sorts of the previous section are based on betas estimated from returns over the previous year and a future one-month return holding period. These are typical estimation and holding periods used in the empirical asset pricing literature. In the section, we aim to examine the robustness of our results to different beta estimation periods and future return holding periods following Bollerslev, Li, and Todorov (2016).

In Table 8 we report results, on univariate portfolios sorted by $\beta_{\Delta JTINsc}$, based on shorter 3-, 6- and 9-months estimation periods (L) and longer 3- and 6-months holding periods (H). In all cases examined, the high-low quintile portfolio average excess return is negative varying between -2.12% (Panel I) and -6.00% (Panel A) per year. Although, average returns are insignificant, risk-adjusted returns with respect to the Fama and French (1993) 3-factor model are statistically significant across all regressions. The significance of the results for longer horizons highlights the persistence in the cross-sectional predictability.

The results reported in the last two sections are in stark contrast with those of Cremers, Halling and Weinbaum (2015). They show that when past betas are used to form quintile portfolios, jump risk premium shift signs from negative to positive. They attribute this finding to time-varying betas, such that using past loadings does not result in consistent exposure to jump risk. Our analysis does not suffer from this problem. This can be attributed to the persistence of our jump risk betas, so that past betas estimates computed on different estimation windows can be considered as good proxies of future jump risk exposure.

2.6 Conclusion

This chapter examines the cross-sectional pricing of stocks according to their sensitivities to option-implied jump risk. We find strong evidence that jump risk is priced in the cross-section of stock returns, and the market price of jump risk is negative. A high-low portfolio sorted by jump risk betas produce a statistically and economically significant negative premium of -9.41% per year. Risk-adjusted returns are also negative and highly significant. Our results also indicate that the negative jump risk premium is due to its downside jump risk component. On the other hand, the premium of the high-low portfolio sorted by upside jump risk betas is not significant. Moreover, this contemporaneous risk-return tradeoff is robust to controlling for betas to innovations in aggregate variance or skewness using dependent bivariate sorts. Finally, our main results carry over to a predictive setting, in which we compare the subsequent realized monthly returns of the quintile portfolios sorted by jump risk betas estimated over the previous period. These results are robust to different beta estimation windows and return holding periods.

The cross-sectional evidence reported in this chapter is in line with the results in the related option pricing and time-series literature. Jump risk constitutes an important determinant not only of option prices and aggregate equity and volatility premium but also impacts the cross-sectional variation of individual stocks expected returns

Figure 2.1. Theoretical and approximated $J_0(T)$ and $EIV_0(T)$ values

This figure presents theoretical and approximated daily values of $J_0(T)$ and $EIV_0(T)$ derived in the simulation study. The theoretical values come from the SVJ model (2.23). The approximated values of $J_0(T)$ and $EIV_0(T)$ are computed from option prices, generated by the SVJ model, based on formulas (2.12) and (2.22), respectively.

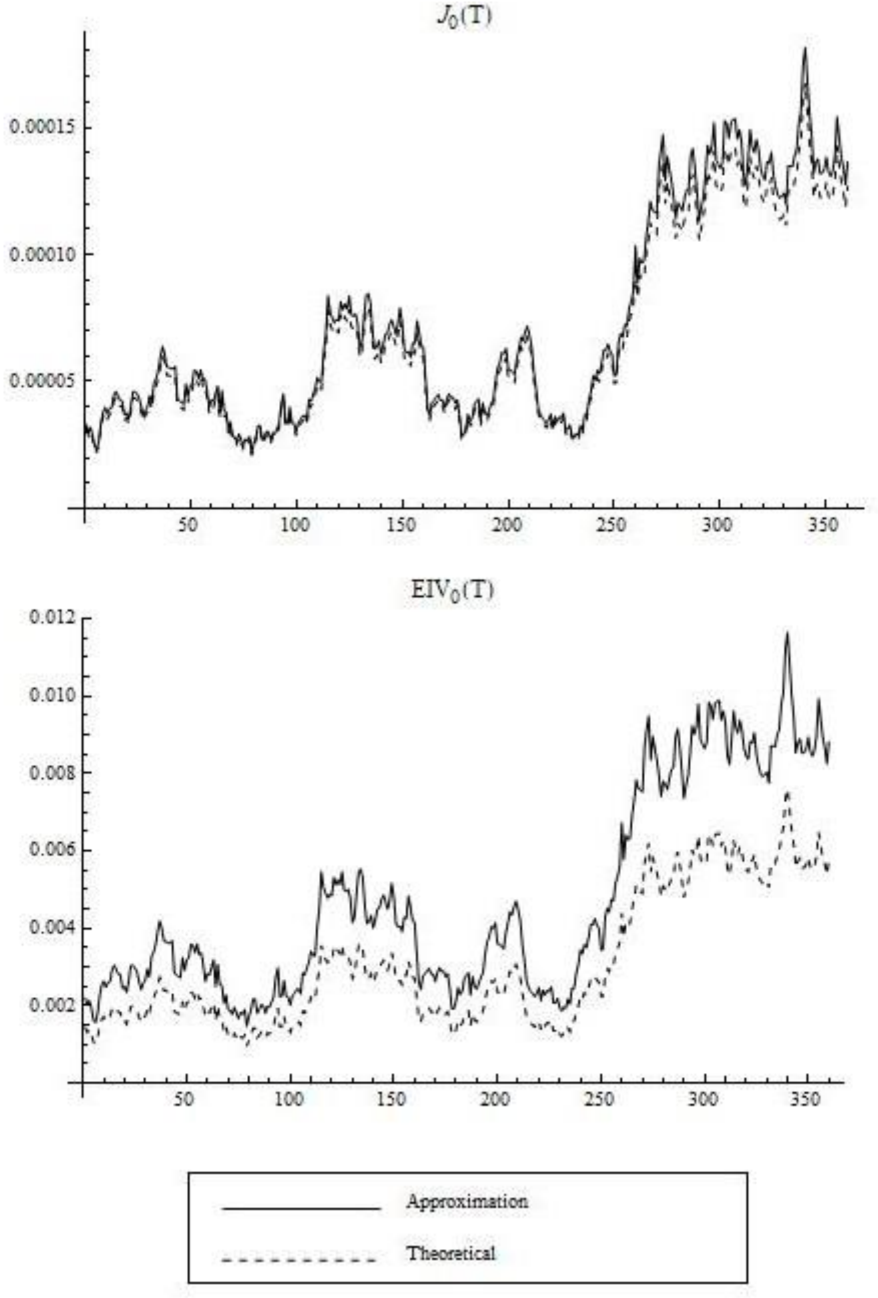

Figure 2.2. Call option delta, vega and gamma derived by SVJ and BS models

This figure presents call option delta, vega and gamma across moneyness levels derived by the SVJ and the BS models. For the BS model the Greeks letters are computed across moneyness using the implied volatility curve.

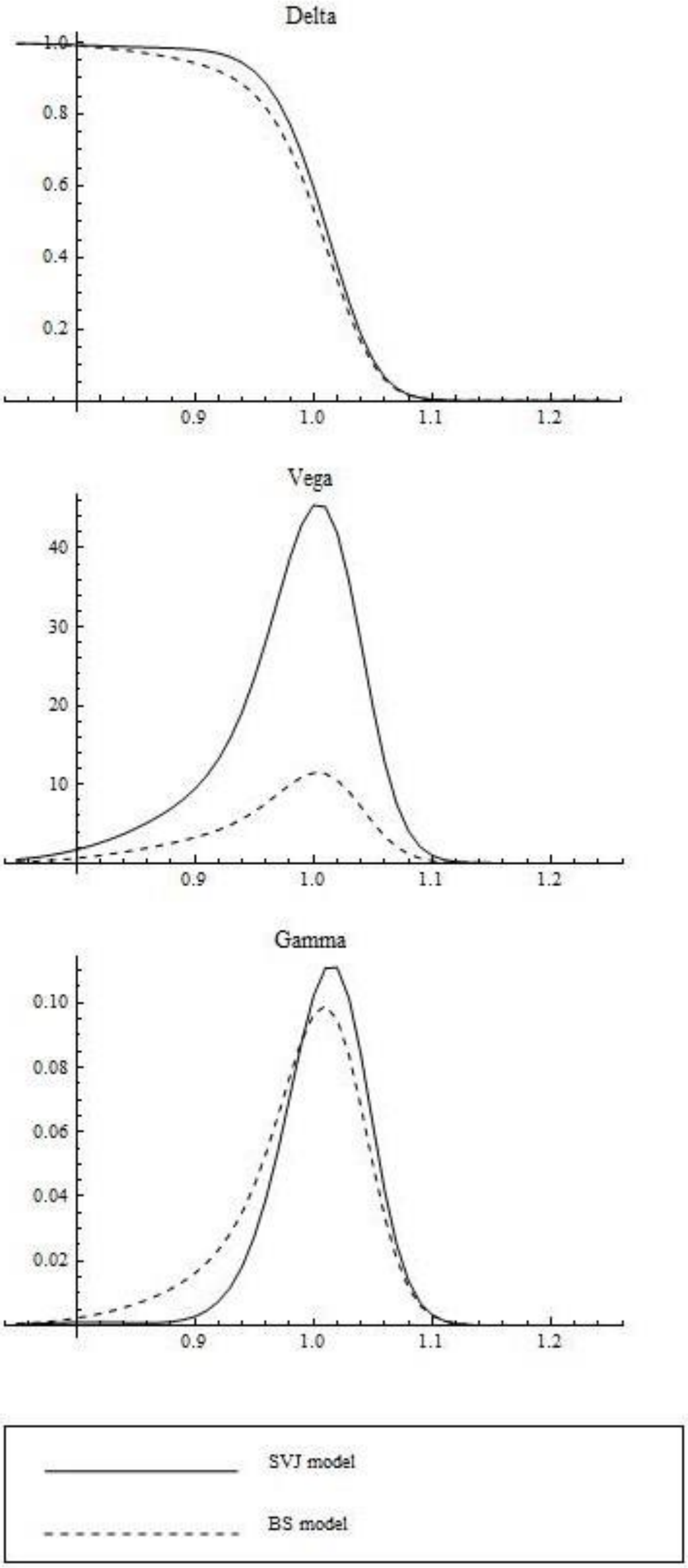

Figure 2.3. Monthly innovations in scaled jump risk measures

This figure shows innovations at a monthly frequency in the scaled jump risk measure $JTIsc$, the scaled downside jump risk measure $JTINsc$, and the scaled upside jump risk measure $JTIPsc$. The sample period is from January 1996 to April 2016.

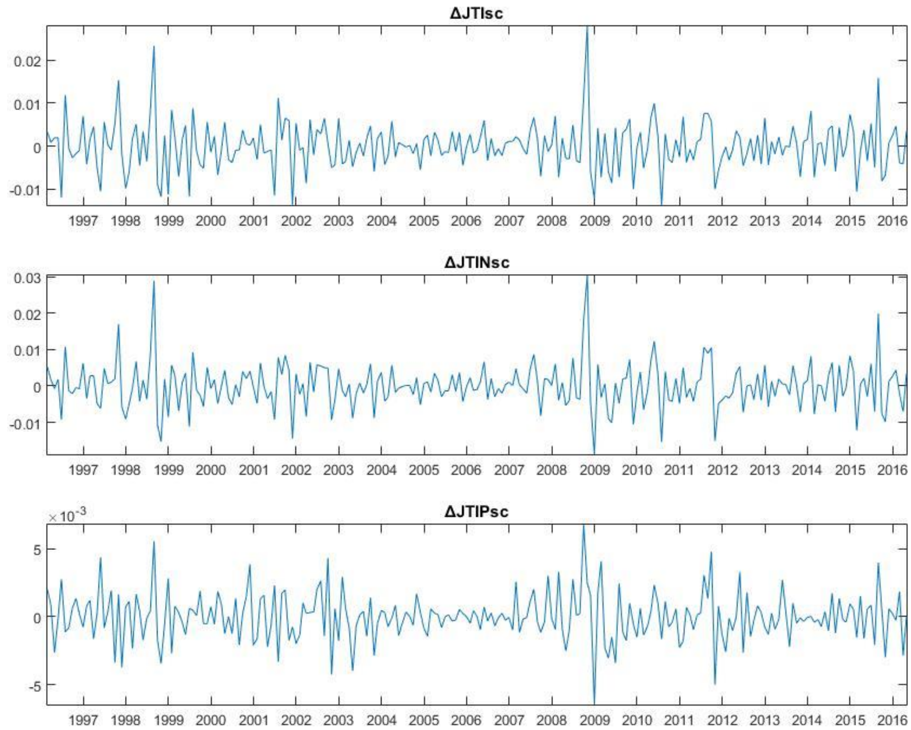

Figure 2.4. Time-series of portfolio betas to scaled jump risk innovations

This figure shows the time-series of the value-weighted average betas for the quintile portfolios sorted by $\beta_{\Delta JTIsc}$, $\beta_{\Delta JTINsc}$ and $\beta_{\Delta JTIPsc}$. The sample period is from January 1996 to April 2016.

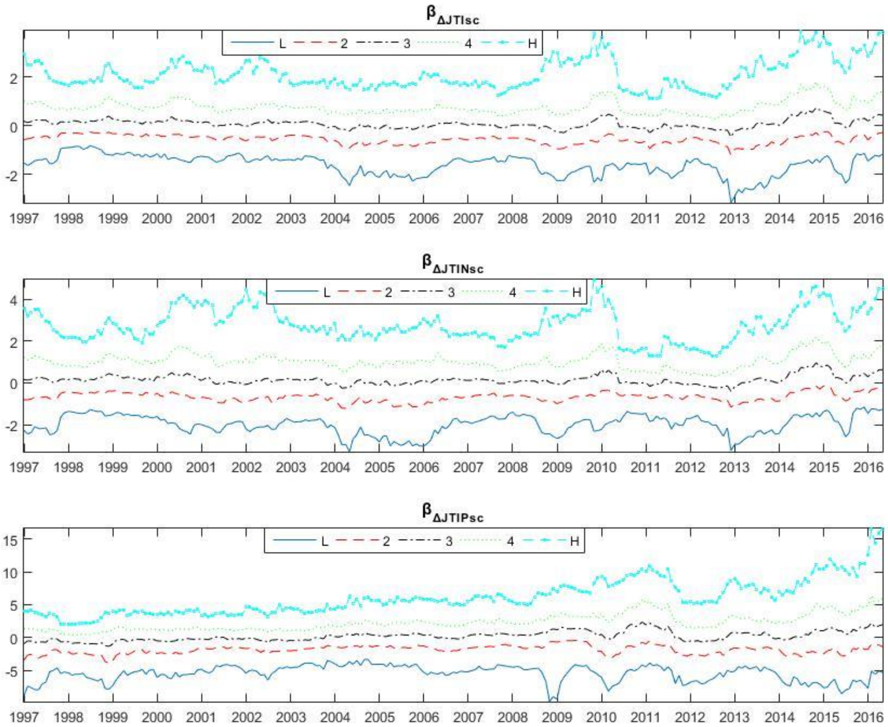

Table 2.1: Simulation study

This table reports the results of our simulation study. Panel A shows average values, and standard deviation (Std) in parentheses, of the theoretical and approximated of $J_0(T)$, $EIV_0(T)$ and of $J_0(T)/EIV_0(T)$ variables. Panel B reports the average values, and standard deviation (Std) in parentheses, of the theoretical and approximated JUMP risk factor. It also reports the same statistics for the delta and vega of the approximated JUMP risk factor. RMSE denotes the root mean squared error, and MPE denotes the mean percentage error between the respective theoretical and approximated variables. The theoretical values of them are implied by the stochastic volatility with jumps model (see formula (2.23)). This model is used to generate call and put option prices at a daily frequency for a 1-year period.

Panel A: Theoretical vs approximated jump components			
		Theoretical	Approximated
$J_0(T)$	Mean	0.0067	0.0072
	Std	(0.0038)	(0.0041)
	RMSE		5.6×10^{-6}
	MPE		6.27%
$EIV_0(T)$	Mean	0.0031	0.0047
	Std	(0.0038)	(0.0026)
	RMSE		0.0018
	MPE		53.59%
$J_0(T)/EIV_0(T)$	Mean	0.022	0.015
	Std	-	(0.0001)
	RMSE		0.0068
	MPE		30.80%
Panel B: Theoretical vs approximated JUMP risk factor			
		Theoretical	Approximated
JUMP	Mean	-0.02	0.14
	Std	(0.61)	(3.91)
	RMSE		4.44
	MPE		2,544%
Delta	Mean	-	0.33
	Std	-	(0.0037)
Vega	Mean	-	8.58
	Std	-	(4.10)

Table 2.2: Summary Statistics for Selected Variables

Panel A presents the mean, standard deviation, skewness, 5%, 50% and 95% percentiles of selected variables, while Panel B presents the correlations of innovations in selected variables and daily excess market returns (MKT), SMB, HML and MOM factors. The sample period is from January 1996 to April 2016.

Panel A: Descriptive statistics

	JTI	$JTIN$	$JTIP$	$JTIsc$	$JTINsc$	$JTIPsc$
Mean	0.0001	0.0001	0.00003	0.0185	0.0271	0.0087
Std	0.0001	0.0002	0.0001	0.0071	0.0090	0.0034
Skewness	3.6685	3.7881	3.8031	1.4375	1.5083	0.9920
Kurtosis	18.3726	19.8564	20.2795	5.7067	5.7179	4.0122
P5	0.0000	0.0000	0.0000	0.0098	0.0165	0.0043
Median	0.0000	0.0001	0.0000	0.0171	0.0248	0.0081
P95	0.0003	0.0004	0.0001	0.0330	0.0454	0.0152

Panel B: Correlation coefficients

	ΔJTI	$\Delta JTIN$	$\Delta JTIP$	$\Delta JTIsc$	$\Delta JTINsc$	$\Delta JTIPsc$	ΔVAR	$\Delta SKEW$	MKT	SMB	HML	MOM
ΔJTI	1											
$\Delta JTIN$	0.95	1										
$\Delta JTIP$	0.51	0.73	1									
$\Delta JTIsc$	0.66	0.50	-0.01	1								
$\Delta JTINsc$	0.81	0.72	0.30	0.92	1							
$\Delta JTIPsc$	-0.04	0.16	0.63	-0.60	-0.27	1						
ΔVAR	0.60	0.67	0.62	0.31	0.50	0.28	1					
$\Delta SKEW$	-0.28	-0.12	0.31	-0.81	-0.58	0.87	0.03	1				
MKT	-0.53	-0.61	-0.64	-0.27	-0.52	-0.41	-0.74	-0.12	1			
SMB	0.00	0.02	0.06	0.00	-0.01	-0.01	0.07	-0.03	0.03	1		
HML	0.00	-0.04	-0.11	0.07	0.05	-0.04	-0.07	-0.05	-0.03	-0.16	1	
MOM	0.09	0.15	0.24	-0.01	0.04	0.10	0.22	0.04	-0.25	0.10	-0.34	1

Table 2.3: Summary Statistics for Betas

Panel A presents the mean, standard deviation, skewness, 5%, 50% and 95% percentiles of stock betas. Panel B presents the time-series average of cross-sectional correlations of stock betas. Panel C presents the autocorrelation coefficients of betas for lags 1, 2, 3, 6, 9 and 12. Betas are estimated every month using daily data from the previous 12 months. The sample period is from January 1996 to April 2016.

Panel A: Descriptive statistics

	$\beta_{\Delta JTIsc}$	$\beta_{\Delta JTINsc}$	$\beta_{\Delta JTIPsc}$	$\beta_{\Delta VAR}$	$\beta_{\Delta SKEW}$
Mean	0.16	0.25	0.10	0.90	-0.001
Std	1.78	2.30	5.50	16.15	0.040
Skewness	0.20	0.24	0.17	0.11	0.017
Kurtosis	4.84	4.83	4.99	5.84	5.302
P5	-2.69	-3.39	-8.75	-24.80	-0.068
Median	0.09	0.14	-0.01	0.36	-0.001
P95	3.22	4.25	9.42	28.28	0.065

Panel B: Correlation coefficients

	$\beta_{\Delta JTIsc}$	$\beta_{\Delta JTINsc}$	$\beta_{\Delta JTIPsc}$	$\beta_{\Delta VAR}$	$\beta_{\Delta SKEW}$
$\beta_{\Delta JTIsc}$	1				
$\beta_{\Delta JTINsc}$	0.95	1			
$\beta_{\Delta JTIPsc}$	-0.65	-0.42	1		
$\beta_{\Delta VAR}$	0.47	0.67	0.23	1	
$\beta_{\Delta SKEW}$	-0.85	-0.69	0.89	-0.09	1

Panel C: Autocorrelations

	$\beta_{\Delta JTIsc}$	$\beta_{\Delta JTINsc}$	$\beta_{\Delta JTIPsc}$	$\beta_{\Delta VAR}$	$\beta_{\Delta SKEW}$
1	0.87	0.87	0.87	0.84	0.87
2	0.75	0.75	0.75	0.71	0.76
3	0.64	0.64	0.64	0.60	0.65
6	0.36	0.36	0.36	0.32	0.37
9	0.13	0.13	0.12	0.11	0.12
12	-0.09	-0.08	-0.09	-0.05	-0.09

Table 2.4: Contemporaneous returns and characteristics of portfolios

This table presents contemporaneous average excess and risk-adjusted returns and betas for value-weighted quintile portfolios. Every month stocks are sorted into quintiles based on their jump risk betas (Panel A), downside jump risk betas (Panel B) and upside jump risk betas (Panel C). Betas are estimated over the previous 12 months. All reported characteristics are contemporaneous with the betas used to construct the portfolio. Alphas are estimated with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags. The sample period is from January 1996 to April 2016.

Portfolio	Return	FF3 alpha	CAR alpha	$\beta_{\Delta JTIsc}$	$\beta_{\Delta JTINsc}$	$\beta_{\Delta JTIPsc}$	$\beta_{\Delta VAR}$	$\beta_{\Delta SKEW}$	β_{MKT}	β_{SMB}	β_{HML}	β_{MOM}
Panel A: Quintile portfolios sorted by $\beta_{\Delta JTIsc}$												
1	13.22	0.71	2.18	-1.62	-1.95	3.05	-6.70	0.03	1.14	0.31	0.24	-0.16
2	13.02	3.54	3.83	-0.57	-0.69	1.06	-2.65	0.01	0.90	0.02	0.16	-0.03
3	11.50	2.32	2.34	0.08	0.09	-0.20	0.04	0.00	0.92	-0.09	0.11	0.00
4	10.34	0.51	0.46	0.77	0.96	-1.28	3.34	-0.01	1.08	0.01	-0.15	0.01
5	3.81	-8.61	-7.62	2.13	2.66	-3.40	9.53	-0.04	1.42	0.34	-0.48	-0.11
5-1	-9.41	-9.32	-9.80	3.75	4.61	-6.45	16.23	-0.07	0.28	0.03	-0.72	0.05
	(-3.24)	(-3.46)	(-3.90)	(36.43)	(35.17)	(-18.11)	(11.33)	(-17.87)	(2.46)	(0.12)	(-5.62)	(0.38)
Panel B: Quintile portfolios sorted by $\beta_{\Delta JTINsc}$												
1	14.14	1.57	3.18	-1.49	-2.00	1.77	-9.44	0.02	1.12	0.36	0.25	-0.18
2	13.54	4.25	4.38	-0.50	-0.68	0.56	-3.45	0.01	0.88	-0.01	0.17	-0.01
3	11.17	1.92	1.98	0.11	0.15	-0.07	0.60	0.00	0.92	-0.05	0.10	-0.01
4	10.10	0.03	0.04	0.76	1.03	-0.75	4.78	-0.01	1.11	-0.02	-0.13	0.00
5	2.62	-10.40	-9.34	2.07	2.78	-2.09	12.62	-0.03	1.45	0.51	-0.46	-0.12
5-1	-11.52	-11.96	-12.52	3.56	4.78	-3.85	22.06	-0.05	0.32	0.15	-0.71	0.06
	(-3.78)	(-4.43)	(-5.08)	(38.58)	(37.32)	(-7.87)	(12.77)	(-18.96)	(2.30)	(0.74)	(-5.41)	(0.39)
Panel C: Quintile portfolios sorted by $\beta_{\Delta JTIPsc}$												
1	8.50	-2.34	-1.60	1.30	1.23	-5.48	-1.74	-0.04	1.29	0.16	-0.54	-0.08
2	11.61	2.51	2.16	0.42	0.39	-1.85	-1.09	-0.01	1.00	-0.03	-0.13	0.04

3	11.57	2.65	2.55	-0.02	-0.02	0.22	-0.28	0.00	0.89	-0.11	0.11	0.01
4	10.71	0.35	1.02	-0.43	-0.36	2.29	0.65	0.01	0.97	0.02	0.21	-0.07
5	8.13	-5.86	-4.69	-1.01	-0.71	6.07	4.28	0.04	1.35	0.40	0.20	-0.13
5-1	-0.37	-3.52	-3.09	-2.31	-1.94	11.55	6.02	0.07	0.06	0.23	0.73	-0.05
	(-0.15)	(-1.61)	(-1.46)	(-17.90)	(-8.35)	(26.32)	(5.69)	(18.18)	(0.76)	(1.26)	(6.83)	(-0.60)

Table 2.5: Contemporaneous returns for dependent double-sorted portfolios

This table presents contemporaneous average excess and risk-adjusted returns of dependent double-sorted value-weighted quintile portfolios. Every month stocks are first sorted into quintiles based on their volatility risk betas (Panel A) or skewness risk betas (Panel B), and then into quintiles based on downside jump risk betas. Betas are estimated over the previous 12 months. All reported characteristics are contemporaneous with the betas used to construct the portfolio. Alphas are estimated with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags. The sample period is from January 1996 to April 2016.

Portfolio	1 (low $\beta_{\Delta JTINsc}$)	2	3	4	5 (high $\beta_{\Delta JTINsc}$)	high – low $\beta_{\Delta JTINsc}$					
						Return		FF3 alpha		CAR alpha	
Panel A: Quintile portfolios sorted first by $\beta_{\Delta VAR}$ and then by $\beta_{\Delta JTINsc}$											
1 (low $\beta_{\Delta VAR}$)	13.34	16.11	15.40	14.46	9.28	-4.06	(-1.17)	0.91	(0.36)	-3.79	(-1.22)
2	14.76	14.47	14.41	13.32	12.61	-2.15	(-1.15)	-0.40	(-0.22)	-2.22	(-1.11)
3	13.57	12.11	11.37	10.76	11.45	-2.12	(-0.97)	-1.33	(-0.63)	-1.74	(-0.99)
4	9.71	10.09	10.56	10.18	5.27	-4.43	(-1.96)	-3.79	(-1.89)	-2.53	(-1.32)
5 (high $\beta_{\Delta VAR}$)	5.19	6.20	5.21	1.13	-1.21	-6.40	(-1.70)	-13.22	(-4.70)	-9.88	(-2.77)
					control	-3.83	(-2.38)	-3.57	(-2.36)	-4.03	(-3.21)
Panel B: Quintile portfolios sorted first by $\beta_{\Delta SKEW}$ and then by $\beta_{\Delta JTINsc}$											
1 (low $\beta_{\Delta SKEW}$)	9.99	10.90	7.22	2.55	-0.78	-10.77	(-2.42)	-17.99	(-5.23)	-17.18	(-4.45)
2	14.69	12.97	11.54	10.94	4.78	-9.91	(-3.46)	-11.19	(-4.11)	-10.46	(-4.00)
3	15.11	14.08	11.79	10.92	6.80	-8.31	(-3.31)	-10.00	(-3.82)	-11.10	(-5.13)
4	15.90	13.74	12.72	11.03	6.17	-9.73	(-3.64)	-10.90	(-3.99)	-11.84	(-5.07)
5 (low $\beta_{\Delta SKEW}$)	9.81	13.68	13.66	10.19	5.52	-4.29	(-0.98)	-0.36	(-0.09)	-5.47	(-1.27)
					control	-8.60	(-3.42)	-10.09	(-3.82)	-11.21	(-5.08)

Table 2.6: Fama-MacBeth cross-sectional regressions

This table presents firm-level Fama-MacBeth (1973) cross-sectional regression results of contemporaneous one-year excess stock returns on $\beta_{\Delta JTINsc}$ and a set of firm characteristics. The firm characteristics that we control for in the econometric specifications include market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), mispricing (MISP), idiosyncratic volatility (IVOL), and illiquidity (ILLIQ). The definition of each variable is provided in Appendix A. All variables are winsorized at the 1% and 99% levels. The time-series average slope coefficients are reported in each row. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags. The sample period is from January 1996 to April 2016.

Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.115	0.171	0.131	0.157	0.161	0.159
	(3.28)	(2.34)	(2.04)	(4.48)	(4.58)	(4.41)
$\beta_{\Delta JTINsc}$	-0.006	-0.007	-0.008	-0.011	-0.010	-0.012
	(-1.73)	(-2.11)	(-2.26)	(-2.86)	(-2.96)	(-3.33)
SIZE		-0.014	-0.011	0.002	0.002	0.002
		(-1.92)	(-1.66)	(0.73)	(0.60)	(0.51)
BM		0.042	0.041	0.017	0.017	0.019
		(2.79)	(2.66)	(1.26)	(1.54)	(1.70)
MOM			-0.078	-0.029	-0.027	-0.025
			(-1.78)	(-1.18)	(-1.16)	(-1.06)
MISP				-0.002	-0.002	-0.002
				(-4.37)	(-5.36)	(-5.33)
IVOL					-0.225	-0.267
					(-0.42)	(-0.45)
ILLIQ						0.001
						(0.43)

Table 2.7: Predictive single-sorted portfolios

This table presents one-month ahead average excess and risk-adjusted returns of value-weighted quintile portfolios. Returns are reported in annual basis. Every month stocks are sorted into quintiles based on their jump risk betas (Panel A), downside jump risk betas (Panel B) and upside jump risk betas (Panel C). Betas are estimated over the previous 12 months and portfolio returns are computed over the following month. Each portfolio is held for one month. Alphas are estimated with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags. The sample period is from January 1996 to April 2016.

Portfolio	Return	FF3 alpha	CAR alpha
Panel A: Quintile portfolios sorted by $\beta_{\Delta JTIsc}$			
1	11.28	1.92	2.16
2	10.44	2.52	2.28
3	8.64	0.48	0.48
4	7.08	-2.16	-2.04
5	7.08	-5.4	-4.08
5-1	-4.2	-7.32	-6.24
	(-1.00)	(-2.22)	(-1.74)
Panel B: Quintile portfolios sorted by $\beta_{\Delta JTINsc}$			
1	10.80	1.92	1.80
2	10.08	2.04	1.68
3	9.60	1.44	1.44
4	6.24	-3.00	-2.64
5	7.56	-5.40	-3.48
5-1	-3.24	-7.32	-5.40
	(-0.73)	(-2.26)	(-1.50)
Panel C: Quintile portfolios sorted by $\beta_{\Delta JTIPsc}$			
1	9.36	-1.68	-1.56
2	7.80	-0.48	-0.72
3	8.64	0.48	0.60
4	9.72	0.72	0.96
5	11.04	0.36	1.80
5-1	1.56	2.04	3.36
	(0.43)	(0.54)	(0.89)

Table 2.8: Predictive single-sorted portfolios with different beta estimation and return holding periods

This table presents H-month ahead average excess and risk-adjusted returns of value-weighted quintile portfolios. Returns are reported in annual basis. Every month stocks are sorted into quintiles based on their downside jump risk betas. Betas are estimated over the previous L months and portfolio returns are computed over the following H months. Alphas are estimated with respect to the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags. The sample period is from January 1996 to April 2016.

Portfolio	Return	FF3 alpha	CAR alpha	Return	FF3 alpha	CAR alpha	Return	FF3 alpha	CAR alpha
		Panel A: 9 L 1 H			Panel D: 9 L 3 H			Panel G: 9 L 6 H	
1	11.88	2.52	2.64	10.48	1.00	1.44	10.80	1.00	1.50
2	9.96	1.68	1.20	10.28	2.00	2.00	10.06	1.78	2.00
3	9.48	1.08	0.84	9.44	0.92	0.76	8.94	0.58	0.72
4	7.68	-1.68	-1.32	7.92	-1.44	-1.08	7.50	-1.82	-1.62
5	5.88	-7.08	-5.16	7.16	-5.52	-4.00	7.06	-4.78	-3.08
5-1	-6.00	-9.60	-7.80	-3.32	-6.52	-5.44	-3.74	-5.78	-4.58
	(-1.52)	(-3.22)	(-2.38)	(-0.92)	(-2.25)	(-1.66)	(-1.19)	(-2.46)	(-1.58)
		Panel B: 6 L 1 H			Panel E: 6 L 3 H			Panel H: 6 L 6 H	
1	11.16	1.20	1.68	11.20	1.12	1.92	10.94	0.60	1.20
2	10.92	2.52	2.16	10.36	1.52	1.40	10.16	1.36	1.32
3	9.84	1.56	1.20	10.00	1.36	1.24	9.64	1.10	1.24
4	7.32	-2.28	-2.16	8.28	-1.48	-1.20	8.00	-1.50	-0.86
5	5.64	-6.84	-5.40	8.92	-4.36	-2.80	7.98	-4.30	-2.54
5-1	-5.40	-8.04	-6.96	-2.28	-5.48	-4.72	-2.96	-4.90	-3.74
	(-1.31)	(-2.46)	(-1.97)	(-0.63)	(-1.92)	(-1.56)	(-1.03)	(-2.12)	(-1.28)
		Panel C: 3 L 1 H			Panel F: 3 L 3 H			Panel I: 3 L 6 H	
1	10.32	0.12	1.08	10.08	-0.20	0.80	10.54	-0.38	0.22
2	10.20	1.56	1.56	10.44	1.40	1.64	10.12	1.08	1.30

3	10.20	1.56	1.20	9.84	1.24	1.04	9.84	1.10	1.06
4	8.28	-1.20	-1.44	8.68	-0.60	-0.24	8.18	-1.26	-0.58
5	7.08	-5.04	-3.36	6.88	-5.24	-4.36	8.42	-3.78	-2.18
5-1	-3.36	-5.16	-4.44	-3.20	-5.00	-5.16	-2.12	-3.40	-2.40
	(-1.04)	(-1.89)	(-1.52)	(-1.27)	(-2.15)	(-2.11)	(-1.01)	(-1.86)	(-1.06)

Chapter 3

Concave Implied Volatility Curves Prior to Earnings Announcements

3.1 Introduction

Quarterly earnings announcements are scheduled corporate events that disseminate substantial fundamental information to investors. A voluminous literature has examined a number of features related to these events, such as the behavior of stock returns (see, inter alia, Ball and Brown, 1968; Beaver 1968; Ball and Kothari, 1991; Frazzini and Lamont, 2007) and systematic risk (see, for example, Patton and Verardo, 2012; Savor and Wilson, 2016) around these announcements.

A related literature has examined the behavior of equity option prices and implied volatilities (IVs) around earnings announcement days (EADs), identifying three stylized features. First, at-the-money (ATM) IV tends to increase in the runup to the EAD, as uncertainty builds up before this information event, and second, ATM IV sharply decreases right after the announcement, when the related uncertainty is resolved (see Patell and Wolfson, 1979; 1981). More recently, Dubinsky and Johannes (2006) and Dubinsky et al. (2019) have documented a third interesting feature; the term structure of ATM IV becomes downward sloping prior to EADs, meaning that ATM IV is higher for options with shorter expiries than for options with longer expiries.

Building upon this literature, our study documents a novel feature with far reaching implications for our understanding of the behavior of stock prices, the pricing of earnings risk and the informational content of option prices. We show that a large fraction of IV curves extracted from short-expiry equity options systematically become concave in the run up to EADs. In our sample of very large and liquid firms, we find that up to 37.4% of IV curves exhibited concavity just before the announcement during the period 2013-2019. This compares to just 3.5% of IV curves exhibiting concavity on a typical trading day when option expiry does not span an EAD.

The concave IV curves we document are typically inverse U-shaped, S-shaped, or W-shaped. These shapes are in stark contrast with the convex volatility "smiles" and "smirks" (or "skews") that are commonly observed for equity options, where out-of-the-money (OTM) puts trade at higher volatility relative to ATM options. Interestingly, the feature of concavity mostly disappears right after the announcement, as the uncertainty surrounding this event is resolved, and the IV curve reverts to its standard convex shape.

An important observation we make is that a concave IV curve reflects a bimodal Risk-Neutral Distribution (RND) for the underlying stock price. Bimodality in the central part of the RND indicates that, subject to a minor risk-adjustment due to the very short option expiry, the prevailing stock price will most likely be around either of the two identified modes. Hence, a bimodal RND reveals that discrete price movements of certain magnitude are highly anticipated by investors due to the forthcoming announcement. These movements can be considered as anticipated jumps in the continuous-time path of the underlying stock price. To this end, we argue that a concave IV curve provides a clear option-based signal of impending event risk for the underlying stock.[14] This feature is entirely different from the common modelling assumption of a low-probability, randomly timed Poisson jump, which can lead to an IV "smirk" and a left-tailed RND, capturing tail risk and explaining the expensiveness of OTM puts (see, for example, Bates, 1996; 2000; Pan, 2002).

Moreover, concavity appears in short- rather than long-expiry options. This feature arises due to the relative effect between the anticipated jump and the diffusion

[14] According to Liu et al. (2003, p. 231), event risk is defined as "the risk of a major event precipitating a sudden large shock to security prices and volatilities".

component of the underlying stock price process. As expiry shrinks, the effect of the anticipated jump dominates the effect of the diffusion component; this renders the underlying RND bimodal and the IV curve concave. On the other hand, as the expiry increases, the diffusion component dominates, the RND reverts to unimodality and the IV curve to convexity. The sparsity of short-term equity options prior to our sample period can provide an explanation why this feature has not been previously documented.

Having documented these novel features, we formally define an indicator variable for a concave IV curve and examine its informational content. Our analysis reveals that concave IV curves possess significant predictive ability with respect to stock returns on EAD and post-EAD realized volatility. First, we find that, on average, firms exhibiting concave IV curves yield an absolute abnormal stock return of 6% on EAD, which is 1.8% higher than the corresponding absolute return for firms with non-concave IV curves. Second, we find that firms with concave IV curves exhibit an average realized stock return volatility of 45.9% p.a. in the 10-day interval after the announcement, which is 11.05% higher than the corresponding realized volatility of firms with non-concave IV curves.

These findings show that investors are able to identify earnings announcements that trigger larger than average stock price movements and volatility. Anticipating these effects, investors trade accordingly in the option market, giving rise to concave IV curves and bimodal RNDs, which in turn signal ex ante the impending event risk.

The most obvious way investors could speculate on or hedge against large stock price swings on EADs, regardless of their direction, is by purchasing straddles. Delta-neutral ATM straddles have been commonly used to capture the price of volatility risk for the underlying stock returns (Coval and Shumway, 2001; Bakshi and Kapadia, 2003). Therefore, we examine whether delta-neutral straddle returns on EADs differ across concave and non-concave IV curves. Interestingly, we find that, on average, concave IV curves are followed by a 6.17% lower delta-neutral straddle return on EAD, as compared to non-concave IV curves. Hence, even though larger than average stock price movements occur following the formation of concave IV curves, these are not sufficiently large to offset the high cost of purchasing straddles on these occasions. In other words, we show that in the presence of concave IV curves, investors typically pay a significantly higher premium to hedge against the uncertainty caused by the forthcoming announcement.

To directly show that ATM straddles are particularly expensive in the presence of concave IV curves, we introduce a simple measure of their expensiveness. Specifically, we compute the ratio of the sum of the ATM put and call prices divided by the underlying stock price. Intuitively, this ratio indicates the required percentage change in the underlying stock price, in either direction, to offset the cost of the ATM straddle. Hence, this ratio is termed as the *implied move* for the underlying stock price. The higher (lower) the value of this ratio, the more (less) expensive it is to purchase an ATM straddle, ceteris paribus.

We find that, on average, the implied move prior to the EAD is 2.31% higher for non-concave IV curves. This strongly significant differential confirms that ATM straddles are much more expensive prior to EADs in the presence of concave IV curves. This finding can help explain why these straddles yield lower returns on EADs despite the larger than average absolute stock returns observed following the formation of concave IV curves. This finding also provides an alternative way to illustrate that investors pay a significantly higher premium to hedge against the event risk that is signalled by a concave IV curve prior to the announcement.

Our study contributes to various strands of the literature. Starting from the early studies of Patell and Wolfson (1979; 1981), there is a growing literature showing that option-based measures embed significant information prior to earnings announcements (see, inter alia, Amin and Lee, 1997; Ni et al., 2008; Xing et al., 2010; Billings and Jennings, 2011; Barth and So, 2014). We add to this literature by showing, for the first time, that the curvature properties of the IV curve contain significant predictive ability over stock returns, realized volatility, and straddle returns around EADs.

Our setup is related to Dubinsky et al. (2019), who also examine the impact of predictably timed EAD price jumps on option pricing. However, their focus is on the term structure of ATM IV prior to announcements. whereas we examine the curvature properties of the IV curve for short-term equity options. Importantly, in their model, the EAD jump size is assumed to be normally distributed and its mean is a transformation of volatility. As a result, the only effect of this anticipated price jump is a large increase in short-term ATM IV, leading to a downward sloping term structure prior to the announcement. The distribution of stock prices remains unimodal and, specifically, lognormal in the simplified version used to define the proposed term structure estimator; the jump has no effect on the shape of the IV curve across moneyness levels. Therefore, the model of Dubinsky et al. (2019) cannot reproduce the novel but pervasive empirical features we document in our study, namely concavity in the IV curve and bimodality in the RND of the underlying stock price prior to the announcement.

Our study is also related to the literature showing that stock prices do jump upon the release of news in the form of pre-scheduled macroeconomic (see, for example, Savor and Wilson, 2013) or earnings announcements (see Lee and Mykland, 2008; Lee, 2012). Contributing to this literature, our study shows that large stock price movements are systematically anticipated by investors prior to the announcement and they can be detected ex ante because they dramatically affect the pricing of short-expiry options. A fortiori, in the case of concave IV curves, we show that large stock price movements are not just a possibility due to the announcement, but rather a very likely outcome. This feature gives rise to a bimodal short-term RND for the underlying stock price (and return), which is in stark contrast with the established paradigm in asset pricing that relies on unimodal return distributions.

Last but not least, our findings are consistent with the demand-based option pricing framework of Garleanu et al. (2008) and the related evidence in Bollen and Whaley (2004) and Ni et al. (2008). In our setting, anticipating large stock price movements due to the impending announcement, investors are motivated to trade options in a certain range of strikes, for hedging or speculative reasons. In the absence of perfectly elastic supply of options, market makers require a premium to be counterparties in these trades. Hence, this trading activity leads to higher option prices and implied volatilities for the corresponding range of strikes, giving rise to a concave IV curve, which in turn reflects a bimodal RND for the underlying asset price.

3.2 Data and Methodology

3.2.1 Option Data and IV Curves

We construct IV curves using option data sourced from OptionMetrics during the period 2013-2019. For each calendar year, we select the 100 firms with the highest option trading volume, requiring the underlying to be common stock (share codes 10 or 11) with share price higher than $5. This yields a total sample of 178 firms during the entire period. The choice of the sample period and the cross-section of firms are dictated by the availability of short-term option data. Weekly equity options have been actively traded for a range of strikes only in the last decade. Hence, OptionMetrics provides very sparse data for short expiries prior to 2013.

Our primary focus is on option-implied information related to earnings announcements, so we utilize short-term options whose expiry spans the EAD. In particular, we keep options with expiry between 3 and 13 calendar days ahead. We source information on the timing of quarterly EADs from I/B/E/S. Following common practice in the literature (see Barth and So, 2014; Michaely et al., 2014), if the announcement is made after the market close, the next trading day is defined as the EAD.

To ensure that the information embedded in IV curves is meaningful, we apply a number of standard filters to the option data. Specifically, we discard options with zero open interest, zero trading volume, zero bid price, midquote price less than $0.125, non-standard settlement or missing implied volatility. We also discard options that violate standard arbitrage bounds or when the bid is higher than the ask price. To ensure that our findings are not driven by particularly illiquid options, we also discard options when the bid-ask spread is higher than 20% of the midquote price.

To construct the IV curve, we utilize the (annualized) IVs of ATM and OTM options provided by OptionMetrics. To avoid an artificial jump at the ATM region, which could arise from ATM puts potentially trading at higher IV relative to ATM calls, we follow the blending approach of Figlewski (2010). Specifically, we blend the IVs of puts and calls whose strike price K lies within ±2% of the underlying spot price into a single point as follows:

$$IV_{blend}(K) = aIV_{put}(K) + (1-a)IV_{call}(K), \tag{3.1}$$

where $a = (K_{high} - K)/(K_{high} - K_{low})$ and K_{high} (K_{low}) is the highest (lowest) strike in this ±2% range. To ensure a good coverage of the moneyness range, after the blending we require at least 6 options for a given expiry, with at least 2 puts and at least 2 calls.

Equipped with these IV points, we fit a quintic spline using the function *spaps* in MATLAB.[15] This yields the smoothest IV curve in the moneyness space K/S, where S is the current stock price, subject to a tolerance level for the sum of squared errors between the actual and the fitted IVs. In the spirit of Bliss and Panigirtzoglou (2002, 2004), the quintic spline minimizes the following objective function:

$$\rho \sum_{i=1}^{N} [IV(K_i) - \widehat{IV}(K_i;\theta)]^2 + \int_{-\infty}^{+\infty} S^{(3)}(x;\theta)^2 dx, \tag{3.2}$$

where $IV(K_i)$ is the actual implied volatility for strike K_i, $\widehat{IV}(K_i;\theta)$ is the corresponding fitted implied volatility, which is a function of the parameter set θ that defines the quintic spline $S(\theta)$, and ρ is a smoothing parameter that is optimally selected to ensure that the sum of squared IV errors does not exceed a given tolerance level.[16]

Having imposed a number of strict filters on the option data, we seek to fit well the actual IV points, and hence we opt for a low tolerance level. This tolerance level corresponds to a 0.01% mean square error between the actual and the fitted IVs. However, to ensure that the fitted IV curve is not too erratic and does not correspond to an ill-behaved RND, we impose further conditions. We require that no interpolated

[15] A quintic spline ensures that the third derivative of the IV curve (and hence the option price function) is continuous, yielding a well-behaved RND (see Figlewski, 2010).

[16] Parameter ρ controls the tradeoff between the goodness-of-fit and the smoothness of the spline function; the latter is captured by its integrated squared third derivative. Setting a low tolerance level ensures that the spline fits well the actual IV points at the expense of smoothness. To the contrary, setting a high tolerance level yields a rather smooth spline that may not fit well the actual IV points.

IV point is negative and that the corresponding RND does not exhibit a negative density point or more than two modes.[17] If any of these conditions is violated, we increase the upper bound of the mean square error in steps of 0.005% until the conditions are met.

Applying these data filters and implementing the described methodology, we construct 1,875 IV curves on the trading day prior to EAD for the firms in our sample.

3.2.2 Definition of Concave IV Curve

Having constructed a smooth IV curve that fits well the actual IV points, we turn our focus on its shape. IV curves for equity options typically exhibit a “smile” or a “smirk” (see, inter alia, Rubinstein, 1994; Toft and Prucyk, 1997; and the review of the early literature in Jackwerth, 2004), which corresponds to a convex IV curve where OTM puts trade at higher IV than ATM options. This pattern corresponds to an important deviation from the Black and Scholes (1973) model, where implied volatility should be constant across moneyness levels.

In sharp contrast to the commonly documented convex IV curves for equity options, we often observe concave IV curves prior to EADs (see Section 3.1). To capture this phenomenon in a systematic way, we introduce a definition of concavity based on the first and second derivatives of the fitted IV curve with respect to moneyness.[18] Specifically, we define an IV curve to be concave when the following three conditions hold. First, the second derivative of the fitted IV curve is negative for a continuous

[17] To compute the RND corresponding to the fitted IV curve, we use the standard result of Breeden and Litzenberger (1978). The density function is given by $f(K) = e^{rT}\partial^2 C/\partial K^2$, where r is the interest rate and C is the call option price as a function of the strike price K. The fitted IV curve contains 1,001 IV points. These IVs are converted to call option prices using the Black-Scholes formula. In the absence of a continuum of strikes, we compute the second partial derivative in the above formula using finite differences and derive the RND for the range of the available moneyness levels.

[18] First and second derivatives of the fitted IV curve are computed using finite differences.

moneyness (K/S) range of at least 0.03 points, i.e., for a continuous range of strikes that amount to at least 3% of the underlying spot price. Second, we require that the fitted IV curve exhibits a stationary point within the moneyness range where it exhibits concavity. Third, this stationary point is located between the second lowest (K_{min+1}) and the second highest (K_{max-1}) strikes of the *actual* IV points used to fit the smooth IV curve.

These conditions alleviate the potential concern that the documented concavity may be an artefact of outliers or the employed smoothing spline. In particular, they ensure that our definition does not simply capture very local infection points or marginally concave parts of the IV curve. They also ensure that the concavity does not arise from the lowest or highest actual strikes, which typically correspond to deep OTM options.

This definition is sufficiently general to capture various shapes of concavity, such as the inverse U-shape, W-shape, and S-shape IV curves illustrated in Figure 1. Using this definition, we define the dummy variable *CONCAVE*, which takes the value 1 when the IV curve is concave and zero otherwise.

3.2.3 Other Variables and Data Sources

In addition to *CONCAVE*, we use a number of other variables in the subsequent empirical analysis. The definition of these variables is provided in Appendix D. For each firm, we compute at the daily frequency its market beta (*BETA*), the natural logarithm of market capitalization (*LN(SIZE)*) and stock price (*LN(PRICE)*), 5-day cumulative stock return (*RUNUP*), momentum return (*MOM*), stock turnover ratio (*STOCKTR*), and idiosyncratic volatility (*IVOL*). The source of stock prices, trading volumes and number of outstanding shares is CRSP. With respect to firm fundamentals, we utilize the book-to-market value ratio (*B/M*) and the leverage ratio (*LEVERAGE*) using quarterly data from COMPUSTAT. We also use the number of analysts providing earnings forecasts (*NUMEST*), the standard deviation of these forecasts (*DISPERSION*), and the differential stock beta around EADs (*ANNBETA*) as in Barth and So (2014). Analysts forecast data are obtained from I/B/E/S.

We also use a number of option-based variables. Specifically, we compute the ATM implied volatility (*ATMIV*) and the difference between the realized volatility and *ATMIV* (*RVIV*) of Goyal and Saretto (2009). Since our focus is on short-expiry options, we construct *ATMIV* and *RVIV* utilizing the 10-day volatility surfaces that have been recently introduced by OptionMetrics. In addition, we compute the Risk-Neutral Skewness (*RNS*) and Risk-Neutral Kurtosis (*RNK*), following the approach of Bakshi et al. (2003). We also use the option-to-stock trading volume ratio (*O/S*) of Roll et al. (2010). Last but not least, we compute the term structure estimate of ATM implied volatility (*TSIV*) proposed by Dubinsky et al. (2019) as the difference between short- and long-term ATM implied volatilities. Equity option prices, implied volatilities and trading volumes are sourced from OptionMetrics.

3.2.4 Summary Statistics

Table 1 presents the summary statistics for the variables used in our analysis. Their values are computed on the day prior to EAD and they are winsorized at the 1% and 99% levels. We report that 37.4% of the IV curves extracted prior to the EAD exhibit concavity. These IV curves are computed from short-term options, with an average *EXPIRY* of 6.47 calendar days and a large number of *STRIKES* (average=16.72 strikes). The latter feature is consistent with the fact that our sample consists of very large firms, with an average (median) market capitalization of $56,387 ($66,171) million. As a result, these firms exhibit a much lower degree of *IVOL* (average=24.17% p.a.), they trade at a much higher price (average=$75.94), they exhibit low *B/M* ratios (average=0.35), and they are followed by a very large number of analysts (average=24.32), as compared to the corresponding values typically encountered in studies that utilize the entire CRSP universe.

With respect to option-based variables, the median *RNS* (*RNK*) value is -0.26 (3.42), illustrating that these moments do not take substantially different values just before the EAD. To the contrary, in line with the arguments of Patell and Wolfson (1979; 1981), *ATMIV* is substantially higher prior to EADs, with an average value of 42.31%

p.a.. As a consequence, *RVIV* takes very large negative values, with an average of -16.68% p.a.. Moreover, *TSIV* is almost always positive, with an average value of 6.58% p.a.. This confirms the arguments of Dubinsky et al. (2019) that the term structure of ATM implied volatility is downward sloping prior to EADs. Last but not least, we report substantial stock trading activity prior to the EAD, with an average daily *STOCKTR* value of 2.27%, and an even higher trading activity in the option market, with an average *O/S* value of 27.09%.

Table 2 reports the pairwise correlations among these variables. Our main focus is on the correlation properties of the newly proposed variable *CONCAVE*. Most notably, we find that *CONCAVE* is positively correlated with *IVOL*, *ATMIV*, *RNS*, and *TSIV*, whereas it is negatively correlated with *RNK* and *RVIV*. Hence, concave IV curves are associated with higher levels of ATM implied volatility and a steeper downward sloping IV term structure prior to EAD. Moreover, *CONCAVE* exhibits a positive correlation with *STOCKTR*, *O/S* and *NUMEST*, which indicates that concave IV curves more often appear when there is substantial coverage by financial analysts as well as high trading activity by investors prior to the announcement.

However, it should be noted that the reported correlations for *CONCAVE* are not particularly high (mostly, much less than 0.40 in absolute value), alleviating the potential concern that *CONCAVE* may simply mimic another firm characteristic. To the contrary, Table 2 illustrates the extremely high pairwise correlations between *ATMIV*, *RVIV*, *TSIV*, *IVOL*, and *LN(SIZE)* prior to EADs.

Table 3 compares the average values of these variables across observations of concave and non-concave IV curves on the day prior to EAD. We find that concave IV curves are extracted from sets of options with a somewhat shorter average expiry and a higher average number of available strikes. We also find that concave IV curves are associated with firms that, on average, are followed by more analysts, they are relatively smaller, and they exhibit lower *B/M* and *LEVERAGE* ratios.

Moreover, we observe that concave IV curves are associated with significantly higher average values of *BETA*, *IVOL*, *STOCKTR* and *O/S* as well as higher average stock prices and returns (*LN(PRICE)*, *RUNUP*, *MOM*) prior to the EAD. Consistent with the pairwise correlations presented in Table 2, we also report that concave IV curves are accompanied, on average, by significantly higher *ATMIV*, *RNS*, and *TSIV* values and significantly lower *RNK* and *RVIV* values relative to non-concave IV curves.

3.3 Features and Determinants of IV Curves

3.3.1 Features of Concave IV Curves

This Section illustrates the main features of concave IV curves observed in the data. Figure 1 provides examples of the three main types of concavity we encounter in our sample. Panel A shows an inverse U-shape IV curve, where the IV of OTM calls and puts is substantially lower than the IV of ATM options. This shape is in stark contrast with the well-known U-shape IV curve ("smile"), where OTM calls and puts exhibit higher IV than ATM options. Interestingly, such an inverse U-shape IV curve is mentioned in Hull (2009, p. 398), who describes it as a "frown" and provides a textbook example how this shape could arise in equity options.

Panel B of Figure 1 illustrates an S-shape curve exhibiting two stationary points. In this particular example, the concave part of the curve is located in the OTM calls region, whereas the OTM puts region exhibits a typical convex shape. An interpretation of this shape is that concavity arises in a specific moneyness range, where options are trading at higher volatility relatively to neighbouring strikes.

Panels C and D provide examples of an even more intriguing type of concavity, a W-shape IV curve. This shape exhibits three stationary points, with a U-shape curve followed by an inverse-U shape curve, which is in turn followed by another U-shape curve. Here, concavity arises in specific ranges of moneyness, with near-the-money options trading at volatility levels as high as, or even higher than, deep OTM options.

The above shapes of concavity systematically appear in short-expiry equity options just before EADs. Interestingly, these shapes typically disappear right after the announcement, with the IV curve reverting to a standard convex shape. Figure 2 illustrates this pattern using as example the earnings announcement of Apple that took place right after the market close on 28th October, 2013. Whereas the IV curve extracted just before the announcement from options with 4 days to expiry exhibits a clear W-shape, it reverts to a "smile" on the following day using options with the same expiry date. This illustration alleviates the potential concern that the concave shapes we uncover may be an artefact of our methodology to fit the IV curve or the use of very short-expiry options.

Figure 3 further illustrates that IV curves often become concave in the runup to the EAD but they subsequently revert to their standard convex shape. Specifically, Figure 3 reports the fraction of concave IV curves for the firms in our sample on trading days around the EAD *d*. We observe that the fraction of concave IV curves gradually increases from 17.5% on *d*-5 to 25.2% on day *d*-2, reaching the peak of 37.4% on the trading day prior to EAD. Right after the announcement, there is a sharp drop in the fraction of IV curves exhibiting concavity to only 7.8% on *d*. This fraction subsequently drops further and hovers around 4% from *d*+1 onwards.

To emphasize how uncommon it is to find a large fraction of concave IV curves using options whose expiry does not span an EAD, we perform the following analysis. For the firms in our sample, we impose the same data filters and follow the same steps of the methodology described in Section 2 to compute *CONCAVE* on all trading days during the period 2013-2019. We extract 72,736 firm-day IV curves from short-term options whose expiry does not span an EAD. We find that only 3.5% out of these observations exhibit a concave IV curve. This finding further alleviates the potential concern that the large faction of concave IV curves we identify in the runup to the EAD may be an artefact of our methodology or the use of very short-expiry options.

The main variable of interest in our analysis (*CONCAVE*) is defined with respect to the properties of the IV curve. Interestingly, the shape of the IV curve is a reflection of the properties of the RND for the underlying stock price. For example, a symmetric volatility "smile" corresponds to a leptokurtic RND, whereas a volatility "smirk" (or "skew") is associated with a negatively skewed RND (see the related discussion in Jackwerth, 2004; and Hull, 2009, ch. 18).

Figure 4 illustrates that a concave IV curve reflects a bimodal RND for the underlying stock price. This is a rather unusual feature. Practically, RND bimodality implies that at option expiry, the underlying stock will most likely trade around either of the two identified price modes.[19] Panel B of Figure 4 illustrates the RND for the stock price of Amazon, extracted from options with 8 days to expiry on 26th April, 2018, i.e., just before the earnings announcement that took place right after the market close. Whereas the closing stock price was $1,517.96 on that day, the 8-day RND reveals two price modes at expiry; one at $1,444.8 (i.e., 4.8% lower) and the other one at $1,602 (i.e., 5.5% higher). Following the announcement, Amazon's stock price exhibited a positive return of 3.6% on 27th April and closed at $1,580.95 (i.e., 4.15% higher) on 4th May.

Another interpretation of RND bimodality prior to an EAD, as illustrated in Figure 4, is that a discrete price movement or jump is anticipated due to the forthcoming announcement. Interestingly, the textbook example of Hull (2009) argues that a concave, inverse U-shape IV curve reflects a bimodal RND for the underlying asset price, which in turn arises "when a single large jump is anticipated". In sum, we argue that a bimodal RND and a concave IV curve provide option-based signals of impending event risk in the underlying stock. Our analysis reveals that earnings announcements frequently give rise to event risk, which is priced in the option market, and hence can be detected *ex ante*.

RND bimodality is an important feature that distinguishes our study from Dubinsky et al. (2019). The model introduced by the latter study allows for predictably timed price jumps on EADs. However, by assuming a normally distributed EAD jump size, their implied RND remains unimodal, and hence their model cannot reproduce the concave IV curves observed in the data.

Last but not least, we find that concave IV curves predominantly appear in short expiry options. Figure 5 illustrates an example of fitted IV curves for Amazon across different expiries (8, 22, 36, and 50 days) on 26th April, 2018. Whereas the IV curve for the 8-day expiry clearly exhibits a W-shape type of concavity, this feature is much less obvious for the 22-day expiry and disappears for longer expiries.[20]

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[19] It should be noted that the RND indicates risk-neutral probabilities rather than physical probabilities. However, since we utilize firm-level options with very short expiries, the adjustment from risk-neutral to physical probabilities is expected to have only a minor effect.

[20] Data on short-expiry equity options are sparsely available prior to 2013, offering a practical reason why this feature has not been documented in the prior literature.

Intuitively, these patterns arise due to the relative effects of the anticipated stock price jump on EAD versus the diffusion component of the underlying process. As expiry shrinks, the effect of the anticipated price jump dominates the effect of the diffusion component, rendering the underlying RND bimodal and the IV curve concave. To the contrary, as time to expiry increases, the effect of the diffusion component dominates the effect of the anticipated price jump, the RND reverts to unimodality, and the IV curve becomes convex. This Figure further illustrates the different focus of our study relative to Dubinsky et al. (2019). Whereas the latter study argues that the term structure of ATM IV is downward sloping prior to EADs, a feature that Figure 4 clearly illustrates, our focus is on the shape of the entire IV curve extracted from short-expiry options.

3.3.2 Determinants of Concave IV Curves

This Section examines how concave IV curves are related to a number of firm characteristics prior to EADs. Specifically, we run logistic regressions of *CONCAVE* on sets of contemporaneously measured variables. This constitutes a more formal analysis relative to the pairwise correlations reported in Table 2, allowing us to simultaneously consider multiple variables and to test for the statistical significance of these relationships. Table 4 presents the corresponding results. We report z-statistics based on two-way clustered standard errors, at the quarter- and firm-level. This choice is motivated by the arguments of Petersen (2009) and the potential concern that the innovations of the utilized variables may be strongly correlated across quarters and across firms. All models include *BETA*, *LN(SIZE)*, *B/M*, *LEVERAGE*, as well as *EXPIRY* and *STRIKES*.

The estimates of Model (1) show that IV curves extracted from options with shorter expiry and larger number of strikes are significantly more likely to be concave. Moreover, firms that are relatively smaller and less leveraged are also more likely to exhibit a concave IV curve prior to the EAD. Model (2) adds several return-based characteristics. The main finding is that a higher level of *IVOL* is significantly associated with a concave IV curve.

Model (3) includes a number of option-based variables. We find that a concave IV curve is more likely to be observed as *ATMIV* increases and as *RVIV* decreases.[21] We also find that the probability of observing a concave IV curve significantly increases with higher values of *RNS* and lower values of *RNK*. The latter findings are consistent with the observation that concave IV curves reflect bimodal RNDs, as illustrated in the right Panel of Figure 4. Bimodality in the central part of the RND yields a more symmetric and less leptokurtic distribution, as compared to the commonly observed negatively skewed and fat-tailed RNDs, which correspond to convex IV curves.

Model (4) includes firm characteristics that are considered to be proxies of fundamental uncertainty with respect to the forthcoming earnings announcement. Notably, we find that a concave IV curve more likely arises as the number of analysts following the firm increases. Last, Model (5) considers stock and option-to-stock trading activity. We report that a higher *O/S* value prior to the EAD is a significant determinant of concave IV curves.

Despite the highly significant contemporaneous relationship between *CONCAVE* and a number of firm characteristics, none of the reported models yields a very high pseudo R-squared. This feature further alleviates the potential concern that *CONCAVE* may be simply mimicking existing firm characteristics or their combinations.

[21] *TSIV* is almost perfectly negatively correlated with *ATMIV*, and hence they cannot be both included in a regression model. Nevertheless, we have alternatively included *TSIV* instead of *ATMIV* in Model (3). The results confirm that a concave IV curve is more likely to appear as *TSIV* takes higher values.

3.4 The informational content of CONCAVE

3.4.1 Absolute Stock Returns on EAD

We now turn our focus on the informational content of *CONCAVE*. We first examine whether concave IV curves can predict higher or lower absolute stock returns on EAD relative to non-concave IV curves. To ensure that our results are not affected by market-wide price movements or systematic factor-related returns, we use the absolute *abnormal* stock return on EAD (*ABSEADABRET*) with respect to the Fama-French-Carhart (FFC) 4-factor model.

Specifically, we compute the abnormal stock return on EAD as the realized minus the expected return. The expected return is calculated on the basis of pre-estimated factor loadings for each firm from the following regression model:

$$xr_{i,t} = \alpha_i + \beta_{MKT,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}WML_t + \varepsilon_{i,t}, \quad (3.3)$$

where $xr_{i,t}$ denotes the excess stock return of firm *i* on day *t*, *MKT* denotes the excess market return, *SMB* denotes the size factor return, *HML* denotes the value factor return, and *WML* denotes the momentum factor return.[22] To estimate this model, we use daily returns from *d*-250 to *d*-25, where *d* is the EAD, requiring at least 200 observations. This choice ensures that the estimated factor loadings are not affected by stock returns observed in the runup to the EAD.

The summary statistics reported in Table 1 show that the average value of *ABSEADABRET* is 4.84%, whereas the median value is 3.42%. These statistics are consistent with the finding in prior literature that stock prices often exhibit very large movements around earnings announcements (see Lee and Mykland, 2008; Lee, 2012; Kapadia and Zekhnini, 2019). This feature becomes even more striking if one takes into account that our sample consists of very big capitalisation firms.

Table 5 presents estimates from predictive panel regressions of *ABSEADABRET* on *CONCAVE* plus a number of firm characteristics measured on the day prior to the

[22] Daily *MKT*, *SMB*, *HML*, and *WML* returns are sourced from Kenneth French's online data library.

EAD.[23] Models (1), (3), and (5) report *t*-statistics based on two-way clustered standard errors, at the firm- and quarter- level. Models (2), (4), and (6) include quarterly fixed effects to ensure that our results are not entirely driven by specific quarters in our sample period.

Overall, the results in Table 5 show that concave IV curves observed prior to EADs predict significantly higher *ABSEADABRET* values. Column (1) shows that, on average, concave IV curves are followed by a 1.8% (t-stat: 5.63) higher absolute abnormal stock return on EAD relative to non-concave IV curves. On average, the latter are followed by a 4.16% *ABSEADABRET*, whereas concave IV curves are, on average, followed by a 5.96% *ABSEADABRET*. This highly significant return differential remains intact when we account for quarterly fixed effects in column (2), confirming that it is not driven by specific quarters in our sample period. Moreover, this differential remains significant when we additionally control in columns (3)-(6) for a number of firm characteristics that may be related to future stock returns.[24]

An interesting interpretation of this predictive relationship is that investors are able to ex ante identify earnings announcements where larger than average stock price movements are observed, and they trade accordingly in the option market. On these occasions, IV curves become concave and the corresponding RNDs for the underlying stock price become clearly bimodal, indicating that a very large stock price movement is likely to be observed on EAD. In fact, the occurrence of larger than average absolute stock returns upon these announcements verifies the informational content of *CONCAVE*.

[23] Following 5th March 2008, OptionMetrics records bid and ask option prices at 15:59 EST. This ensures that the criticism of Battalio and Schulz (2006) on non-synchronicity bias does not apply during our sample period.

[24] Unreported results, which are available upon request, yield very similar conclusions when we alternatively use gross, rather than abnormal, absolute stock returns on EAD.

3.4.2 Post-EAD Stock Return Volatility

Next, we examine the informational content of *CONCAVE* with respect to the post-EAD stock return volatility (*POSTEADVOL*). To this end, we compute the (annualized) 10-day stock return volatility from *d* to *d+9*, according to the standard formula:

$$POSTEADVOL = \sqrt{\frac{252}{N}\sum_{t=d}^{d+9} r_t^2} \tag{3.4}$$

where r_t is the daily log-return.

Whereas *POSTEADVOL* is naturally affected by the magnitude of *ABSEADABRET*, it is conceptually different from the latter because it also captures the stock price fluctuations occurring after the EAD. We opt for a 10-day measurement window in our benchmark results to be consistent with the range of expiries observed in our option sample. Nevertheless, we have repeated the subsequent analysis using alternatively the 5-day and the 21-day post-EAD stock return volatility as dependent variable. The results are very similar to the ones presented in Table 6 and they are readily available upon request.

The mean (median) value of *POSTEADVOL* reported in Table 1 is 38.97% (31.47%) p.a.. Even though we mainly include large capitalization stocks in our sample, we still find that their returns exhibit a high degree of volatility in the 10-day interval right after the earnings announcement.

Table 6 presents estimates from predictive panel regressions of *POSTEADVOL* on *CONCAVE* plus a number of firm characteristics measured on the day prior to the EAD. We find that *CONCAVE* possesses significant predictive ability over *POSTEADVOL* too. Column (1) indicates that concave IV curves are followed by an average *POSTEADVOL* of 45.86% p.a., whereas non-concave IV curves are followed by an average *POSTEADVOL* of 34.81% p.a., yielding a highly significant differential of 11.05% p.a. (t-stat: 5.35). Column (2) confirms that this differential is not purely driven by volatility episodes in certain quarters. This predictive relationship remains significant when we additionally control in columns (3)-(6) for a number of firm characteristics that may also be related to stock return volatility.

The reported predictive ability of *CONCAVE* indicates that investors can identify the announcements that cause a significant increase in post-EAD volatility. As a consequence, they trade in the option market to hedge against or to speculate on this feature, determining prices that correspond to a bimodal RND for the underlying stock return. In turn, an RND that features bimodality in its central part implies, ceteris paribus, a higher degree of variance over the remaining life of the options. Hence, observing higher than average *POSTEADVOL* for concave IV curves verifies the informational content of *CONCAVE*.

3.4.3 Straddle Returns Around EADs

Having established that concave IV curves are typically associated with significantly higher absolute stock returns on EADs and post-EAD realized volatility, as compared to non-concave IV curves, we further examine the behavior of straddle returns around EADs. Anticipating these stock return characteristics, investors could take long positions in ATM straddles to either speculate on or hedge against these large price swings regardless of their direction. In fact, delta-neutral ATM straddle returns have been used to measure the price of volatility risk for the underlying stock returns (see e.g., Coval and Shumway, 2001; Bakshi and Kapadia, 2003).

We firstly examine the returns of delta-neutral ATM straddles (*STRADDLE*) on EAD. Similar to prior literature, we use the nearest-to-the-money pair of call and put options within the moneyness (K/S) range of 0.98-1.02. We buy the straddle at the close of the trading day prior to the EAD and we sell it at the close after the announcement. We use the shortest available options, requiring that they have at least 3 days to expiry when we close the position. The return of the delta-neutral straddle on EAD is given by:

$$r_{straddle} = w_c r_c + (1 - w_c) r_p \tag{3.5}$$

where r_c (r_p) is the return of the call (put) option on EAD. The weight w_c is given by:

$$w_c = -\frac{\Delta_{PUT}/PUT}{\Delta_{CALL}/CALL - \Delta_{PUT}/PUT} \tag{3.6}$$

where Δ_{CALL} (Δ_{PUT}) is the delta of the call (put) provided by OptionMetrics and $CALL$ (PUT) is the corresponding call (put) price. This weight ensures that the straddle is delta-neutral at formation. We have repeated the analysis reported in Table 7 using simple instead of delta-neutral ATM straddle returns. The results, which are readily available upon request, are very similar to the ones reported in Table 7.

The summary statistics reported in Table 1 show that the median *STRADDLE* value on EAD is -14.35%. This finding provides support for the argument that investors most often pay a substantial price to be hedged against the increased volatility and large stock price swings observed around EADs. However, it should be noted that *STRADDLE* exhibits a positively skewed distribution in our sample and its average value is 0.25%.

Table 7 presents estimates from predictive panel regressions of *STRADDLE* on *CONCAVE* as well as a number of firm characteristics measured on the day prior to the EAD. Models (1), (3), and (5) use two-way clustered standard errors, whereas Models (2), (4), and (6) add quarterly fixed effects. We also control for the expiry and the average moneyness of the pair of options used to construct this straddle strategy, ensuring that our results are not driven by these features.

Overall, we find that concave IV curves predict a significantly lower straddle return on EAD. In particular, column (1) shows that concave IV curves are followed by a 6.17% (t-stat: -2.88) lower *STRADDLE* return, as compared to non-concave IV curves. Column (2) shows that the economic and statistical significance of this finding is not driven by specific quarters in our sample period. Furthermore, this predictive relationship remains intact when we additionally control in columns (3)-(6) for a number of firm characteristics that may be related to volatility, and hence the observed *STRADDLE* returns.

The main conclusion from this analysis is that when IV curves become concave, investors most often pay a substantially higher premium to hedge against the larger than average stock price swings that are typically observed on these EADs. In fact, the median *STRADDLE* value is -17.19% when *CONCAVE*=1 and -13.03% when *CONCAVE*=0. In other words, even though larger than average stock price movements occur on EADs following the formation of concave IV curves, these price swings are not large enough to offset the substantial cost of purchasing straddles on these occasions. As a corollary, whereas it is known to be typically profitable to write straddles prior to EADs (see Gao et al., 2018; Dubinsky et al., 2019), we document that is even more profitable to do so when concave IV curves are observed.

To provide direct evidence that ATM straddles are particularly costly in the presence of concave IV curves, we introduce an intuitive measure of their expensiveness. Specifically, we calculate the following ratio:

$$IMPMOVE = \frac{CALL\ +\ PUT}{STOCK} \tag{3.7}$$

where, as above, $CALL$ (PUT) is the ATM call (put) price at straddle formation, i.e., on the day prior to the EAD, and $STOCK$ is the corresponding price of the underlying stock. This measure roughly indicates how much the underlying stock price should move in either direction to offset the cost of a symmetric ATM straddle, and hence it is termed as the implied stock price move (*IMPMOVE*). The higher (lower) the value of *IMPMOVE*, the more (less) expensive it is to purchase an ATM straddle, ceteris paribus.

To construct this measure, we use the same pair of nearest-to-the-money call and put options that we used above to construct the delta-neutral straddle. The summary statistics reported in Table 1 indicate an average (median) *IMPMOVE* value of 6.22% (5.27%). Taking into account that we utilize very short-expiry options, these statistics indicate that ATM straddles are quite expensive prior to EADs, as they require a substantial stock price move in either direction to offset their cost.

Table 8 presents estimates from contemporaneous panel regressions of *IMPMOVE* on *CONCAVE* and a number of firm characteristics measured on the day prior to EAD. Models (1), (3), and (5) use two-way clustered standard errors, whereas Models (2), (4), and (6) add quarterly fixed effects. In unreported results, we have additionally controlled for the expiry and the average moneyness of the pair of options used to compute *IMPMOVE*; the results are very similar to the ones presented in Table 8.

Overall, we find very strong evidence that ATM straddles are much more expensive in the presence of concave IV curves. Specifically, column (1) indicates that concave IV curves are associated with a 2.31% (t-stat: 7.79) higher *IMPMOVE* relative to non-concave IV curves. The average value of *IMPMOVE* is 7.67% when *CONCAVE*=1 and 5.46% when *CONCAVE*=0. This significant differential is not subsumed when we control for quarterly fixed effects or additional firm characteristics in columns (2)-(6).

These findings provide direct evidence that in the presence of concave IV curves, the underlying stock price should exhibit a substantially larger move after the announcement, in either direction, to offset the cost of purchasing the ATM straddle prior to the EAD. This evidence rationalizes why despite the larger than average absolute stock returns realized on EADs following the formation of concave IV curves, the corresponding straddle returns are still much lower relative to non-concave IV curves. This is because these straddles are substantially more expensive to purchase in the first place, and hence the realized price jumps on EADs are not sufficient to offset their cost.

The significantly higher cost of buying ATM straddles in the presence of concave IV curves provides an alternative way to illustrate that investors pay a significantly higher price to hedge against the event risk that arises on these occasions due to the impending announcement. This evidence further corroborates the argument that concave IV curves provide an ex ante signal of event risk. Based on these findings, we conclude that investors can ex ante identify the announcements that trigger large stock price moves and they pay a substantially higher premium to hedge against them, most obviously by purchasing ATM straddles. As a result of this hedging activity, the corresponding ATM options become very expensive, trading at higher volatility, and hence the corresponding IV curves turn concave prior to EADs.

3.5 Conclusions

This study documents, for the first time in the literature, that the IV curves of equity options frequently exhibit concavity prior to the EAD. This shape is in stark contrast with the convex volatility "smiles" or "smirks" that are commonly observed for equity options. Concavity is most obvious in short-expiry options, it reflects a bimodal RND for the underlying stock price, and quickly disappears after the announcement, as the uncertainty surrounding this event is resolved.

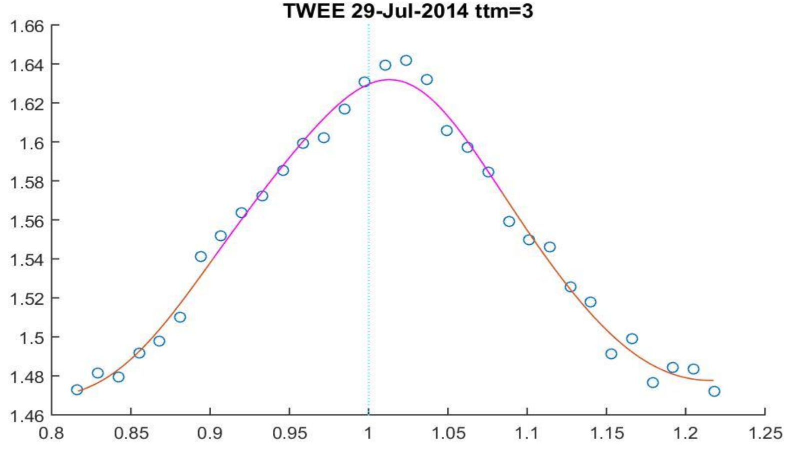
This feature has far reaching implications for our understanding of the behavior of stock prices, the pricing of earnings risk and the informational content of option prices. We report significant evidence that firms with concave IV curves exhibit higher absolute abnormal stock returns on EAD and higher realized volatility after the announcement. Despite the larger than average stock price moves on EAD following the formation of concave IV curves, we still find that the corresponding delta-neutral straddle returns are significantly lower than for non-concave IV curves. To rationalise this finding, we provide strong evidence that ATM straddles are significantly more expensive in the presence of concave IV curves, and hence the realized stock price jumps are not sufficient to offset the substantial cost of these straddles.

Overall, we show that investors can ex ante identify the announcements that trigger larger than average stock price moves and they pay a substantially higher premium to hedge against this event risk. This hedging activity impacts on option prices, leading to the formation of a concave IV curve. To this end, we conclude that concavity in the IV curve constitutes an ex ante option-implied signal for event risk in the underlying stock arising due to the impending announcement.

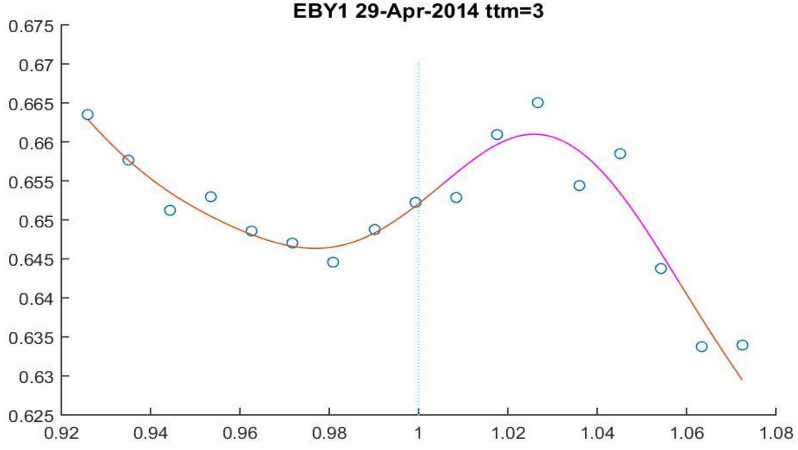
The focus of our study is on scheduled corporate earnings announcements. However, it would be interesting to examine the features and the informational content of IV curves around other, non-corporate events that may also trigger large asset price moves. In fact, prior studies have argued that macroeconomic announcements and geopolitical events can give rise to substantial event risk, which can be ex ante reflected in option prices (see Savor and Wilson, 2013; Leahy and Thomas, 1996; Melick and Thomas, 1997; Kelly et al., 2015; Hanke et al., 2018). We anticipate that the curvature properties of the IV curve around these events can reveal substantial information with respect to the pricing of event risk and the subsequent behavior of asset prices.

Figure 3.1. Types of concave IV curves

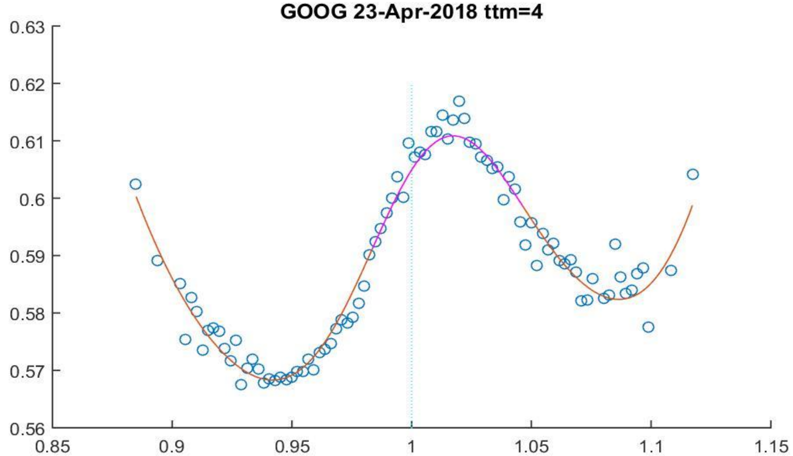
This Figure shows different types of concave IV curves computed on the day prior to the EAD. Panel A shows an example of an inverse U-shape IV curve for Twitter, computed from options with 3 days to expiry on 29th July, 2014. Panel B presents an example of an S-shape IV curve for Ebay, computed from options with 3 days to expiry on 29th April, 2014. Panels C and D present examples of W-shape IV curves for Google and Netflix, computed from options with 4 days to expiry on 23rd April and 16th July 2018, respectively. Circles indicate implied volatilities corresponding to actual traded strikes, whereas the curve is fitted using a smoothing spline.



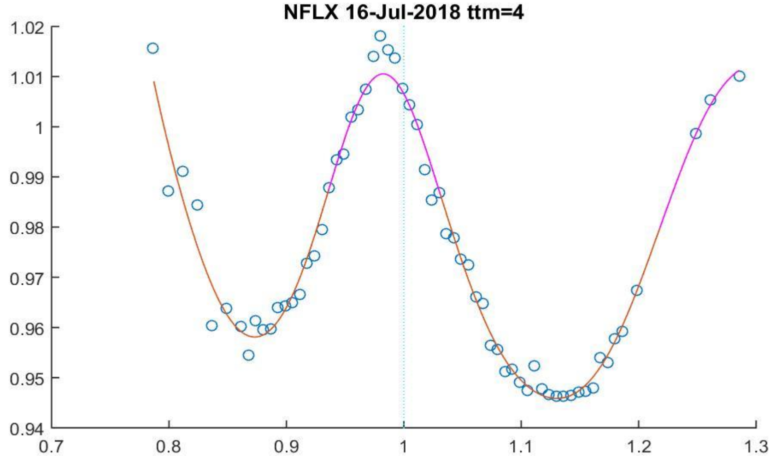
Panel A: Inverse U-shape IV Curve



Panel B: S-shape IV Curve



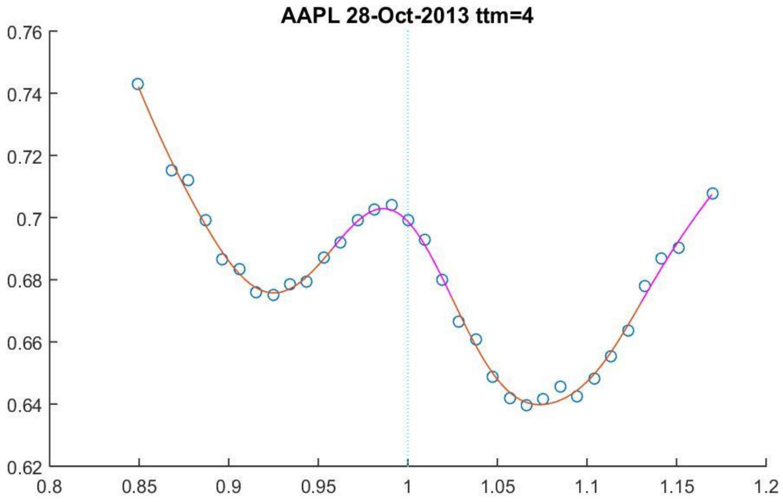
Panel C: W-shape IV Curve



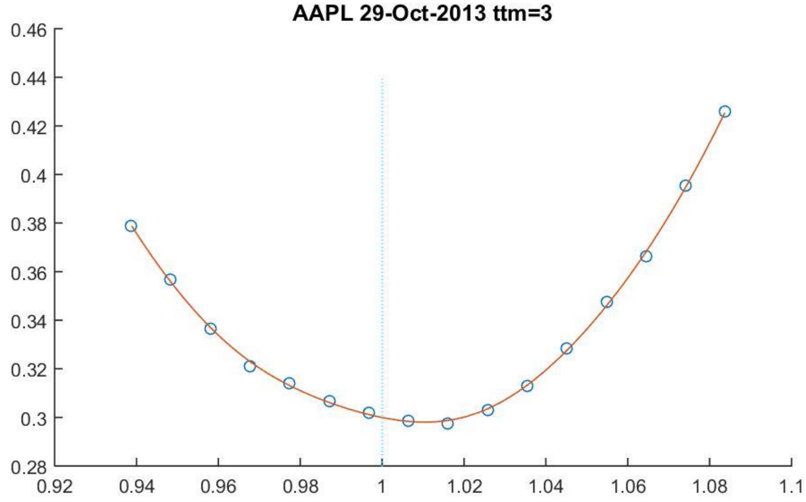
Panel D: W-shape IV Curve

Figure 3.2. Concave IV curves around EAD

This Figure illustrates how a concave IV curve prior to the EAD becomes convex after the announcement. Panel A presents a concave IV curve for Apple, computed from options with 4 days to expiry on 28th October, 2013, i.e., prior to its quarterly earnings announcement. Panel B presents a convex IV curve for the same firm, computed from options with 3 days to expiry on 29th October, 2013, i.e., right after the announcement.



Panel A: Concave IV curve prior to the announcement



Panel B: Convex IV curve after the announcement

Figure 3.3. Fraction of concave IV curves around EAD

This Figure shows the fraction of firms exhibiting a concave IV curve on each trading day from *d-5* to *d+5*, where *d* is the quarterly EAD. The definition of a concave IV curve is provided in Section 2.2. IV curves are computed for the 100 firms with the highest option trading activity per year during the period 2013-2019.

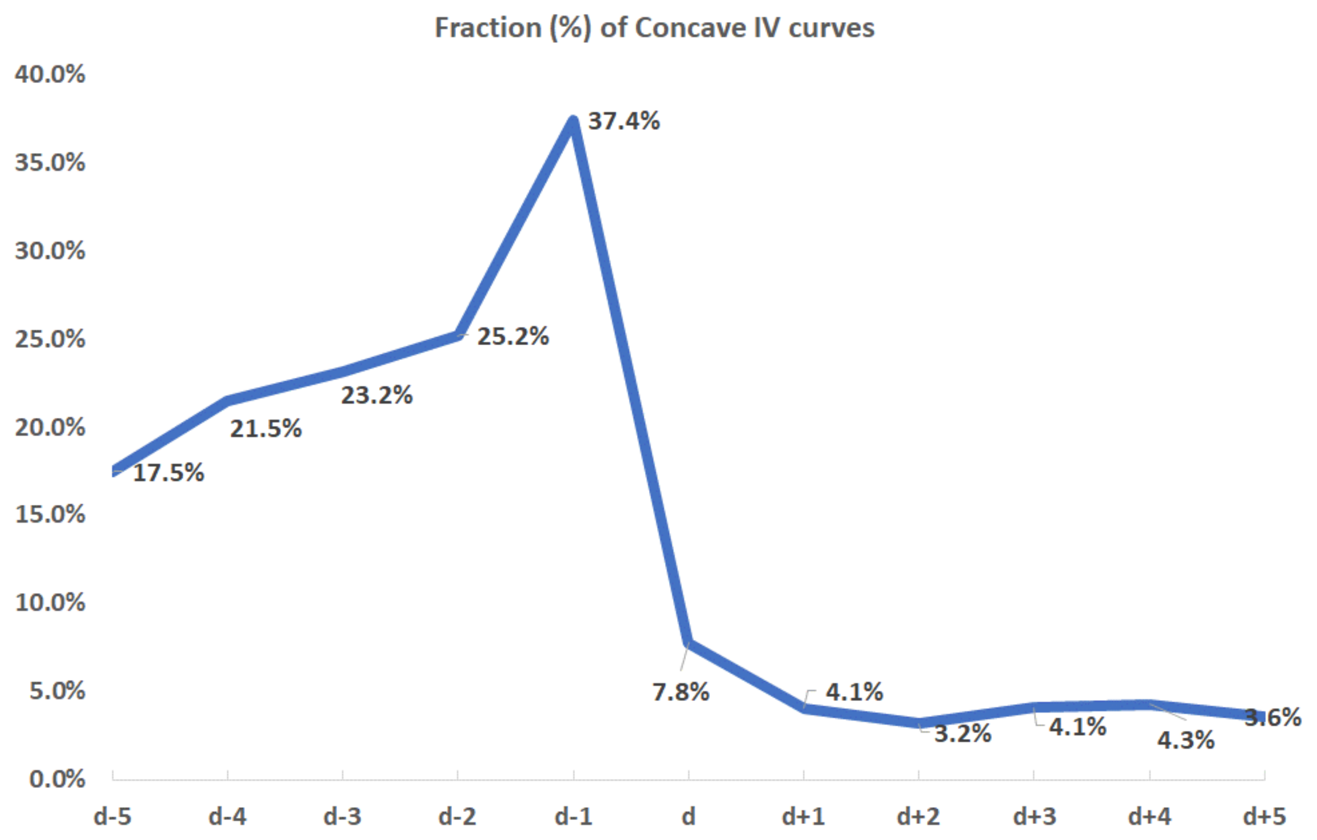
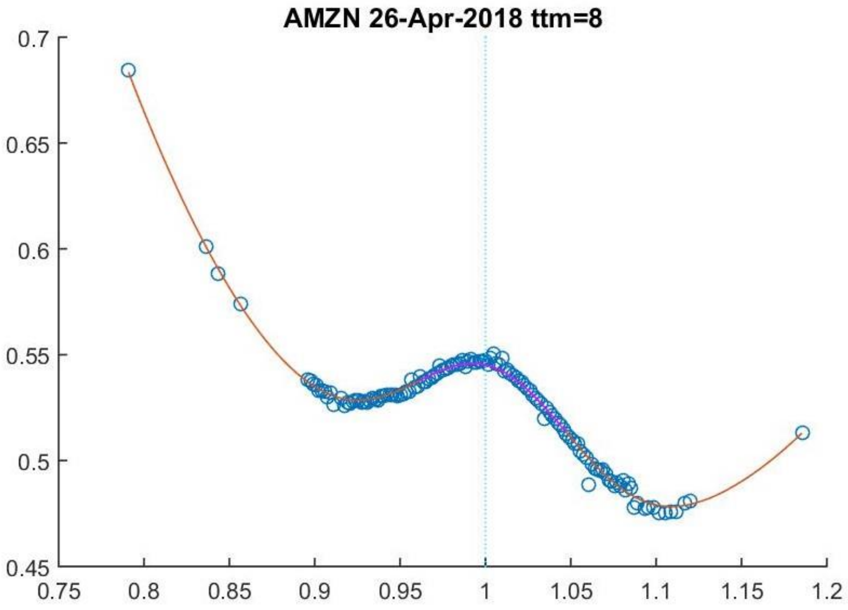
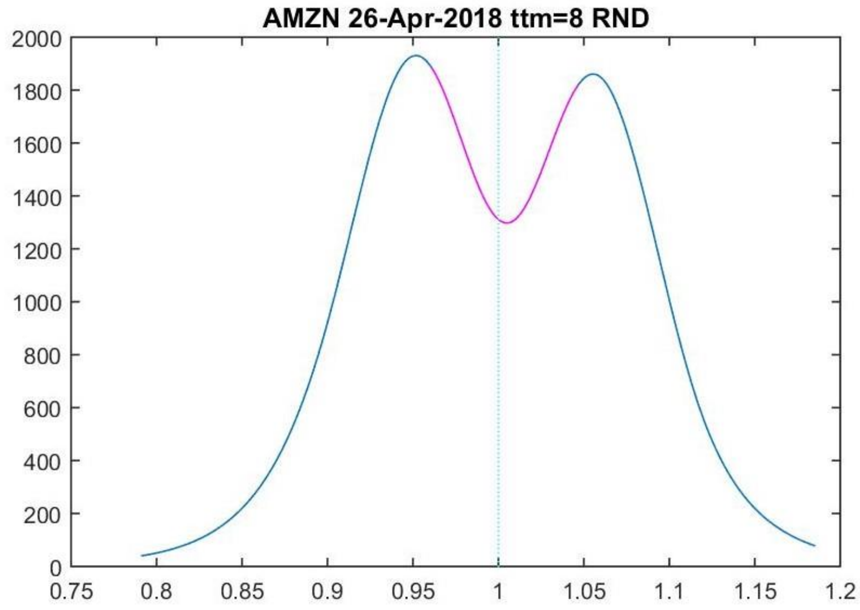


Figure 3.4. Concave IV curves and RND bimodality

This Figure illustrates the correspondence between a concave IV curve and the RND for the underlying stock price. Panel A presents the IV curve for Amazon, computed from options with 8 days to expiry on 26th April, 2018, i.e., just before its quarterly earnings announcement. Circles indicate implied volatilities corresponding to actual traded strikes, whereas the curve is fitted using a smoothing spline. Panel B presents the central part of the corresponding RND for Amazon on the same day. The RND is computed for the range of available strikes using the non-parametric methodology of Figlewski (2010).



Panel A: Concave IV Curve



Panel B: Bimodal Risk-Neutral Distribution

Figure 3.5. IV curves for short- vs longer-expiry options

This Figure shows the shape of IV curves for Amazon, computed from options with different expiries (8, 22, 36, and 50 days to expiry) on 26th April, 2018, i.e., just before its quarterly earnings announcement. The IV curves are fitted using a smoothing spline.

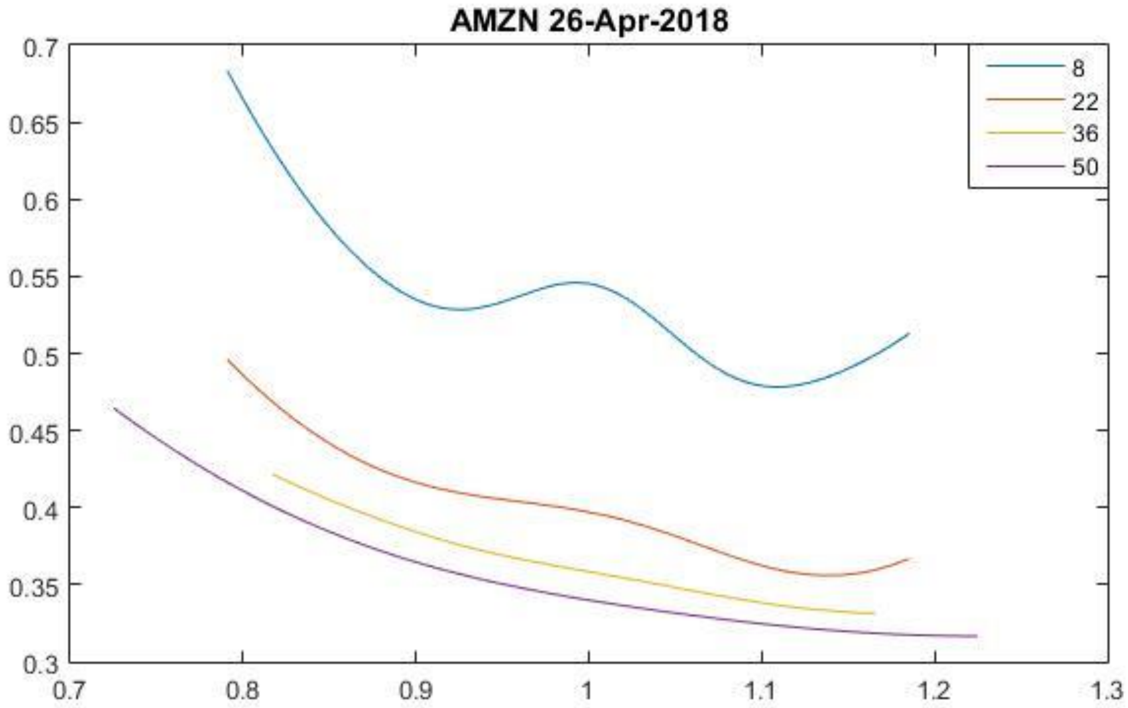


Table 3. 1: Summary statistics

This Table presents summary statistics for selected variables. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. *ABSEADABRET* is the absolute abnormal stock return on EAD, measured with respect to the 4-factor FFC model. *POSTEADVOL* is the 10-day post-EAD annualized realized stock return volatility. *STRADDLE* denotes the return of the delta-neutral ATM straddle strategy on EAD. *IMPMOVE* denotes the ratio of the sum of the ATM put and call prices divided by the underlying stock price. The definition of the rest of the variables is provided in Appendix D. These summary statistics are based on the values of the variables measured on the day prior to the EAD and they are computed for a sample of quarterly earnings announcements during the period 2013-2019.

Variable	**Mean**	**St. Dev.**	**25th pctl**	**Median**	**75th pctl**	**Obs.**
CONCAVE	0.374	0.48	0	0	1	1,875
EXPIRY	6.47	2.61	4	8	9	1,875
STRIKES	16.72	11.83	9	13	20	1,875
BETA	1.09	0.31	0.90	1.09	1.28	1,842
LN(SIZE)	10.94	1.30	10.08	11.10	11.97	1,867
B/M	0.35	0.32	0.13	0.26	0.45	1,760
LEVERAGE	0.34	0.24	0.16	0.27	0.49	1,809
RUNUP	0.43%	3.84%	-1.71%	0.53%	2.56%	1,875
MOM	17.92%	40.92%	-5.49%	12.03%	32.12%	1,842
IVOL	24.17%	12.35%	15.20%	20.55%	29.62%	1,842
LN(PRICE)	4.33	0.90	3.76	4.21	4.77	1,875
ATMIV	42.31%	20.28%	28.13%	35.77%	51.53%	1,825
RNS	-0.28	0.24	-0.43	-0.26	-0.12	1,875
RNK	3.51	0.45	3.22	3.42	3.70	1,875
RVIV	-16.68%	14.30%	-23.08%	-14.74%	-7.67%	1,825
TSIV	6.58%	3.66%	3.87%	5.50%	8.35%	1,867
NUMEST	24.32	7.58	19	24	30	1,867
DISPERSION	12.46%	25.80%	2.43%	4.43%	9.95%	1,860
ANNBETA	0.08	0.80	-0.31	0.06	0.49	1,801
STOCKTR	2.27%	2.88%	0.65%	1.14%	2.57%	1,875
O/S	27.09%	31.69%	5.64%	15.11%	35.35%	1,875
ABSEADABRET	4.84%	4.64%	1.58%	3.42%	6.44%	1,842
POSTEADVOL	38.97%	25.28%	21.77%	31.47%	48.31%	1,872
STRADDLE	0.25%	50.21%	-33.93%	-14.35%	20.30%	1,862
IMPMOVE	6.22%	3.16%	3.96%	5.27%	7.74%	1,863

Table 3.2: Pairwise correlations of firm characteristics

This Table presents pairwise correlation coefficients among selected variables. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. These correlations are based on the values of the variables measured on the day prior to the EAD and they are computed for a sample of quarterly earnings announcements during the period 2013-2019.

	CONCAVE	BETA	LN(SIZE)	B/M	LEVERAGE	RUNUP	MOM	IVOL	LN(PRICE)	ATMIV	RNS	RNK	RVIV	TSIV	NUMEST	DISPERSION	ANNBETA	STOCKTR	O/S
CONCAVE	1																		
BETA	0.09	1																	
LN(SIZE)	-0.19	-0.27	1																
B/M	-0.12	0.22	-0.12	1															
LEVERAGE	-0.21	0.14	-0.03	0.71	1														
RUNUP	0.03	0.04	-0.02	0.01	-0.01	1													
MOM	0.12	0.10	-0.05	-0.19	-0.18	0.05	1												
IVOL	0.29	0.28	-0.76	-0.02	-0.16	0.03	0.19	1											
LN(PRICE)	0.12	-0.12	0.40	-0.34	-0.31	0.07	0.16	-0.25	1										
ATMIV	0.35	0.30	-0.68	-0.06	-0.23	-0.04	0.16	0.84	-0.20	1									
RNS	0.40	0.11	-0.23	0.01	-0.05	0.03	0.09	0.19	-0.03	0.15	1								
RNK	-0.42	-0.08	0.35	0.10	0.21	0.01	-0.10	-0.33	0.08	-0.38	-0.58	1							
RVIV	-0.33	-0.13	0.43	0.09	0.24	-0.02	-0.09	-0.57	0.09	-0.63	-0.19	0.33	1						
TSIV	0.39	0.23	-0.61	-0.15	-0.33	-0.02	0.17	0.78	-0.14	0.94	0.16	-0.41	-0.68	1					
NUMEST	0.20	0.00	0.22	-0.23	-0.40	0.04	0.03	-0.06	0.24	0.10	0.06	-0.14	-0.17	0.19	1				
DISPERSION	0.04	0.16	-0.25	0.08	0.03	0.02	0.03	0.33	-0.02	0.29	0.05	-0.04	-0.16	0.24	-0.09	1			
ANNBETA	0.05	0.11	-0.09	0.05	0.01	0.01	0.06	0.11	0.00	0.11	-0.01	-0.05	-0.09	0.12	-0.08	0.04	1		
STOCKTR	0.27	0.27	-0.65	-0.01	-0.14	0.05	0.23	0.79	-0.09	0.78	0.14	-0.25	-0.48	0.75	0.01	0.29	0.14	1	
O/S	0.27	-0.07	0.02	-0.15	-0.12	0.06	0.06	0.00	0.51	0.04	0.05	-0.04	-0.13	0.10	0.13	-0.04	0.05	0.11	1

Table 3.3: Characteristics of firms with concave vs. non-concave IV curves

This Table presents the average values of selected variables for firms when they exhibit a concave IV curve on the day prior to the EAD (*CONCAVE*=1) versus the corresponding average values when they do not exhibit a concave IV curve (*CONCAVE*=0). The definition of the rest of the variables is provided in Appendix D. The values of the variables are measured on the day prior to the EAD and they are computed for a sample of quarterly earnings announcements during the period 2013-2019. The pre-last column contains the difference in the average values and the last column presents the corresponding *t*-statistic under the null hypothesis of equal means.

Variable	***CONCAVE*=1**	***CONCAVE*=0**	**Difference**	***t*-stat**
EXPIRY	6.08	6.71	-0.63	-5.05
STRIKES	21.30	13.98	7.31	12.22
BETA	1.13	1.07	0.06	3.72
LN(SIZE)	10.64	11.12	-0.48	-7.50
B/M	0.30	0.38	-0.09	-5.77
LEVERAGE	0.27	0.38	-0.10	-9.59
RUNUP	0.68%	0.27%	0.41%	2.18
MOM	23.77%	14.50%	9.27%	4.35
IVOL	28.55%	21.61%	6.94%	11.47
LN(PRICE)	4.44	4.26	0.18	3.79
ATMIV	51.19%	37.02%	14.16%	14.59
RNS	-0.15	-0.36	0.20	21.07
RNK	3.26	3.66	-0.40	-22.22
RVIV	-22.79%	-13.05%	-9.74%	-13.94
TSIV	8.35%	5.52%	2.83%	16.69
NUMEST	26.14	23.22	2.92	7.85
DISPERSION	13.73%	11.71%	2.03%	1.65
ANNBETA	0.11	0.07	0.04	1.03
STOCKTR	3.21%	1.71%	1.49%	10.37
O/S	37.75%	20.71%	17.04%	10.41

Table 3.4: Determinants of concave IV curves

This Table presents the results of contemporaneous logistic regressions of *CONCAVE* on alternative sets of firm characteristics. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. The values of the variables are measured on the day prior to the EAD and they are computed for a sample of quarterly earnings announcements during the period 2013-2019. *z*-statistics are provided in parentheses, using two-way clustered standard errors at the firm- and quarter-level.

	(1)	(2)	(3)	(4)	(5)
EXPIRY	-0.110	-0.114	-0.118	-0.111	-0.028
	(-3.47)	(-3.63)	(-3.62)	(-3.79)	(-0.76)
STRIKES	0.047	0.039	0.046	0.046	0.030
	(4.96)	(3.87)	(5.57)	(5.29)	(3.00)
BETA	0.359	0.294	0.125	0.369	0.344
	(1.65)	(1.37)	(0.74)	(1.58)	(1.49)
LN(SIZE)	-0.317	-0.142	0.313	-0.409	-0.250
	(-3.89)	(-1.29)	(3.31)	(-5.06)	(-2.48)
B/M	0.057	0.047	-0.362	-0.155	0.128
	(0.16)	(0.12)	(-0.98)	(-0.48)	(0.35)
LEVERAGE	-1.641	-1.472	0.201	-0.818	-1.659
	(-3.10)	(-2.86)	(0.40)	(-1.65)	(-3.08)
RUNUP		1.147			
		(0.77)			
MOM		0.045			
		(0.24)			
IVOL		2.481			
		(2.42)			
LN(PRICE)		0.021			
		(0.14)			
ATMIV			2.629		
			(3.43)		
RNS			4.077		
			(8.60)		
RNK			-2.222		
			(-5.74)		
RVIV			-1.592		
			(-2.81)		
NUMEST				0.045	
				(4.42)	
DISPERSION				-0.299	
				(-1.27)	
ANNBETA				0.056	
				(0.61)	
STOCKTR					6.027
					(1.26)
O/S					1.337
					(3.34)
Constant	2.951	0.500	3.146	2.695	1.470
	(2.94)	(0.31)	(1.54)	(2.49)	(1.14)
Clustered SE	Quarter&Firm	Quarter&Firm	Quarter&Firm	Quarter&Firm	Quarter&Firm
Observations	1,733	1,733	1,692	1,687	1,733
Pseudo R-square	12.41%	12.93%	32.39%	14.15%	13.88%

Table 3.5: Concave IV curves and absolute abnormal stock returns on EAD

This Table presents results from predictive panel regressions of the absolute abnormal stock return on EAD (*ABSEADABRET*) on *CONCAVE* and a set of firm-level characteristics measured on the day prior to the EAD. The abnormal stock return is computed with respect to the 4-factor FFC model. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. The sample consists of quarterly earnings announcements during the period 2013-2019. Models (1), (3), and (5), use two-way clustered standard errors, at the firm- and quarter-level. Models (2), (4), and (6), include quarterly fixed effects. *t*-statistics are provided in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
CONCAVE	0.0180 (5.63)	0.0190 (8.56)	0.0086 (3.14)	0.0090 (4.15)	0.0054 (2.18)	0.0054 (2.47)
BETA			0.0028 (0.76)	0.0018 (0.50)	-0.0013 (-0.35)	-0.0032 (-0.91)
LN(SIZE)			-0.0156 (-9.80)	-0.0157 (-17.09)	-0.0156 (-10.59)	-0.0160 (-16.84)
B/M			-0.0187 (-3.60)	-0.0172 (-4.91)	-0.0137 (-2.88)	-0.0117 (-3.38)
RUNUP			0.0341 (1.55)	0.0398 (1.48)	0.0220 (0.95)	0.0293 (1.11)
MOM			-0.0003 (-0.06)	0.0034 (1.25)	0.0003 (0.06)	0.0039 (1.44)
LN(PRICE)			0.0006 (0.25)	0.0006 (0.41)	-0.0003 (-0.13)	-0.0004 (-0.33)
NUMEST					0.0010 (4.28)	0.0011 (7.71)
DISPERSION					0.0114 (1.67)	0.0129 (3.28)
ANNBETA					0.0033 (1.94)	0.0032 (2.54)
Constant	0.0416 (16.55)	-	0.2168 (10.84)	-	0.1974 (10.49)	-
Clustered SE	Quarter&Firm	No	Quarter&Firm	No	Quarter&Firm	No
Fixed Effects	No	Quarter	No	Quarter	No	Quarter
Observations	1,837	1,837	1,733	1,733	1,687	1,687
R-squared	3.52%	5.85%	21.85%	23.84%	23.52%	25.70%

Table 3.6: Concave IV curves and 10-day post-EAD stock return volatility

This Table presents results from predictive panel regressions of the post-EAD realized stock return volatility (*POSTEADVOL*) on *CONCAVE* and a set of firm-level characteristics measured on the day prior to the EAD. Post-EAD volatility is computed using stock returns from *d* to *d*+9, where *d* is the EAD, and it is annualized. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. The sample consists of quarterly earnings announcements during the period 2013-2019. Models (1), (3), and (5), use two-way clustered standard errors, at the firm- and quarter-level. Models (2), (4), and (6), include quarterly fixed effects. *t*-statistics are provided in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
CONCAVE	0.1105 (5.35)	0.1177 (9.97)	0.0443 (2.91)	0.0465 (4.54)	0.0327 (2.42)	0.0312 (3.06)
BETA			0.0798 (3.60)	0.0688 (4.15)	0.0682 (3.14)	0.0529 (3.25)
LN(SIZE)			-0.0953 (-11.17)	-0.0979 (-22.62)	-0.0906 (-11.51)	-0.0952 (-21.35)
B/M			-0.0853 (-3.73)	-0.0690 (-4.17)	-0.0627 (-2.97)	-0.0437 (-2.69)
RUNUP			-0.1671 (-1.24)	-0.0237 (-0.19)	-0.2351 (-1.48)	-0.0712 (-0.57)
MOM			0.0303 (1.48)	0.0583 (4.56)	0.0298 (1.37)	0.0593 (4.67)
LN(PRICE)			-0.0031 (-0.25)	-0.0038 (-0.59)	-0.0060 (-0.61)	-0.0072 (-1.16)
NUMEST					0.0041 (3.29)	0.0045 (6.81)
DISPERSION					0.0902 (3.37)	0.1008 (5.50)
ANNBETA					0.0070 (0.94)	0.0031 (0.54)
Constant	0.3481 (18.94)	-	1.3612 (12.26)	-	1.2165 (11.79)	-
Clustered SE	Quarter&Firm	No	Quarter&Firm	No	Quarter&Firm	No
Fixed Effects	No	Quarter	No	Quarter	No	Quarter
Observations	1,867	1,867	1,730	1,730	1,684	1,684
R-squared	4.49%	8.95%	32.89%	38.59%	33.35%	39.62%

Table 3.7: Concave IV curves and delta-neutral straddle returns on EAD

This Table presents results from predictive panel regressions of delta-neutral ATM straddle returns computed on EAD (*STRADDLE*) on *CONCAVE* and a set of firm-level characteristics measured on the day prior to the EAD. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. Option controls include the expiry and the average moneyness of the options used to construct the straddle strategy. The sample consists of quarterly earnings announcements during the period 2013-2019. Models (1), (3), and (5), use two-way clustered standard errors, at the firm- and quarter-level. Models (2), (4), and (6), include quarterly fixed effects. *t*-statistics are provided in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
CONCAVE	-0.0617 (-2.88)	-0.0578 (-2.22)	-0.0631 (-2.94)	-0.0597 (-2.26)	-0.0666 (-2.69)	-0.0620 (-2.25)
BETA	-0.0541 (-1.62)	-0.0529 (-1.24)	-0.0533 (-1.62)	-0.0537 (-1.25)	-0.0592 (-1.64)	-0.0610 (-1.38)
LN(SIZE)	-0.0411 (-3.58)	-0.0407 (-3.98)	-0.0430 (-4.40)	-0.0427 (-3.82)	-0.0432 (-4.33)	-0.0425 (-3.51)
B/M	-0.0216 (-0.81)	-0.0241 (-0.60)	-0.0220 (-0.78)	-0.0223 (-0.52)	-0.0142 (-0.48)	-0.0108 (-0.25)
RUNUP			0.4276 (2.32)	0.4482 (1.36)	0.4060 (1.95)	0.4353 (1.29)
MOM			-0.0229 (-0.59)	-0.0183 (-0.55)	-0.0250 (-0.58)	-0.0220 (-0.64)
LN(PRICE)			0.0055 (0.46)	0.0061 (0.37)	0.0063 (0.58)	0.0066 (0.39)
NUMEST					0.0006 (0.36)	0.0005 (0.28)
DISPERSION					0.0111 (0.17)	0.0235 (0.47)
ANNBETA					0.0050 (0.36)	0.0132 (0.83)
Constant	0.7523 (0.33)	-	0.6440 (0.28)	-	2.3630 (0.99)	-
Clustered SE	Quarter&Firm	No	Quarter&Firm	No	Quarter&Firm	No
Fixed Effects	No	Quarter	No	Quarter	No	Quarter
Option Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,720	1,720	1,720	1,720	1,674	1,674
R-squared	1.17%	2.88%	1.31%	3.01%	1.35%	3.12%

Table 3.8: Concave IV curves and straddle-implied stock price moves prior to EAD

This Table presents results from contemporaneous panel regressions of the implied move of the underlying stock price prior to the EAD (*IMPMOVE*) on *CONCAVE* and a set of firm-level characteristics measured on the day prior to the EAD. *IMPMOVE* denotes the ratio of the sum of the ATM put and call prices divided by the underlying stock price. *CONCAVE* is an indicator variable that takes the value 1 when the IV curve is concave on the day prior to the EAD and zero otherwise. The definition of the rest of the variables is provided in Appendix D. The sample consists of quarterly earnings announcements during the period 2013-2019. Models (1), (3), and (5), use two-way clustered standard errors, at the firm- and quarter-level. Models (2), (4), and (6), include quarterly fixed effects. *t*-statistics are provided in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
CONCAVE	0.0231 (7.79)	0.0239 (17.01)	0.0131 (6.23)	0.0133 (13.27)	0.0099 (6.15)	0.0094 (10.15)
BETA			0.0102 (2.75)	0.0094 (5.77)	0.0080 (2.56)	0.0064 (4.34)
LN(SIZE)			-0.0145 (-10.96)	-0.0147 (-34.59)	-0.0141 (-13.29)	-0.0143 (-36.13)
B/M			-0.0173 (-4.79)	-0.0154 (-9.50)	-0.0134 (-4.27)	-0.0113 (-7.64)
RUNUP			-0.0484 (-1.88)	-0.0364 (-2.92)	-0.0540 (-1.97)	-0.0384 (-3.41)
MOM			0.0039 (1.67)	0.0084 (6.75)	0.0050 (2.46)	0.0097 (8.44)
LN(PRICE)			-0.0011 (-0.54)	-0.0011 (-1.80)	-0.0017 (-1.11)	-0.0019 (-3.30)
NUMEST					0.0009 (4.62)	0.0010 (15.99)
DISPERSION					0.0134 (2.69)	0.0145 (8.66)
ANNBETA					0.0021 (1.79)	0.0012 (2.34)
Constant	0.0536 (20.16)	-	0.2139 (11.62)	-	0.1900 (14.22)	-
Clustered SE	Quarter&Firm	No	Quarter&Firm	No	Quarter&Firm	No
Fixed Effects	No	Quarter	No	Quarter	No	Quarter
Observations	1,858	1,858	1,721	1,721	1,675	1,675
R-squared	12.47%	17.90%	55.52%	62.02%	60.04%	67.29%

Conclusions

This thesis, composed of three independent empirical studies, examines the informational role of option contracts on future stock returns.

In chapter 1, we create a joint measure tracking the probability density function of individual stock returns. This new measure is an intuitive score variable based on risk-neutral volatility, skewness and kurtosis. Essentially, our measure ranks stocks based on investors' expectations about future return distribution properties and can be interpreted as a defensiveness measure where the definition of defensiveness is expanded by incorporating skewness and kurtosis alongside with volatility. We find that high rank stocks significantly outperform low rank stocks. A portfolio going long the highest decile portfolio and short the lowest decile portfolio yields a statistically significant 0.75% (0.79%) value-weighted (equally-weighted) return and significant alphas, with both legs of the strategy contributing to the overall abnormal return. This relation is robust to various variables proposed in the literature using double sorts and Fama-MacBeth regressions. This relation is not consistent with standard moment preferences, so we provide an alternative explanation building on the ICAPM. We find that high rank stocks are exposed to shocks in aggregate volatility while low rank stocks hedge against these shocks. Moreover, we show that the explanatory power of the ICAPM depends on the level of investors' sentiment. When investors' sentiment is low, the ICAPM can fully explain this relation. In contrast, in high sentiment periods the ICAPM alpha remains positive and significant and is attributed to mispricing. It would be interesting for future research to examine the score measure's predictability constructed from options of longer than 1-month time-to-maturity. Furthermore, in a portfolio management perspective, it would be fascinating to compare the performance of the high-low score portfolio to volatility-managed ones.

In chapter 2, we examine the cross-sectional pricing of equities according to their sensitivities to innovations in option-implied jump risk. We find strong evidence that jump risk is negatively priced in the cross-section of stock returns. We use the Du and

Kapadia (2012) formulas and find that high-low quntile portfolios formed by betas to jump risk and its downside jump component produce significant negative premiums of -9.41% and -11.52% per year contemporaneously, respectively. Notably, this contemporaneous risk-return tradeoff is robust to controlling for betas to innovations in aggregate variance or skewness using dependent bivariate sorts. Lastly, we examine the relation between jump risk sensitivities and future stock returns and show that the hedge portfolio delivers significant abnormal returns in the following month of the portfolio formation, while it is also robust to different beta estimation and holding period windows. The clear conclusion drawn by our results is that jump risk constitutes an important determinant not only of option prices and aggregate equity and volatility premiums but also impacts the cross-sectional variation of individual stocks returns. Future research could be done examining if aggregate volatility (in addition to market return) jump risk, that can be extracted using VIX options, is priced in the cross-section of stock returns.

In chapter 3 we investigate the implied volatility curves that are determined from option prices prior to earnings announcements days. We show, that a fraction of them becomes concave, taking unusual shapes such as W, S, and inverted. This characteristic, which is mostly observed in short-term options, reflects a bimodal risk-neutral density for the stock price and quickly disappears after the earnings announcement day. This pattern is consistent with investors anticipating a jump in the stock price at the earnings announcement day. We find that concave implied volatility curves do predict higher absolute stock returns at the earnings announcement day and higher realized volatility following the earnings announcement day at a 5-, 10- or 21-day interval. However, straddle returns of stocks with concave implied volatility curves are significantly lower than those with non-concave implied volatility curves. We rationalize this finding to the fact that at-the-money options of concave implied volatility curves are much more expensive and the jumps of the stock price at the earnings announcement day are not large enough to offset the substantial cost of these straddles. Therefore, investors identify event risk in stocks that jump in the earnings announcement days and pay a substantially higher premium to hedge against this risk. As a future research, it would be intriguing to investigate whether these patterns in implied volatility curves occur in other firm level events or macro announcements.

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Appendix A

Book-to-Market ratio (B/M): We compute a firm's book-to-market ratio following Fama and French (1993). Book value is the book value of stockholders' equity plus deferred taxes plus investment tax credit minus the book value of preferred stock. Market value is the number of shares outstanding times the price of the stock.

Beta: We estimate the CAPM beta using a 60-month rolling estimation window.

Beta ΔVIX (β ΔVIX): Following Ang, Hodrick, Xing and Zhang (2006), we estimate the beta of market volatility innovations by regressing daily returns of the previous month on VXO first differences.

Expected Idiosyncratic skewness (EIS): We obtain EIS data from Brian Boyer's website.[25] See Boyer, Mitton and Vorkink (2010) for a detailed description.

Gross Profitability (GPROFIT): Following Novy-Marx (2013), we define a firm's gross profitability as annual revenues minus costs of goods sold, divided by total assets.

Idiosyncratic volatility (IVOL): Following Ang, Hodrick, Xing and Zhang (2006), we define idiosyncratic volatility as the standard deviation of residuals of the Fama and French (1993) three-factor model using a one-month rolling window.

Illiquidity (ILLIQ): We compute Amihud's (2002) illiquidity measure in a rolling one year window as: : $ILLIQ_i = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{VOLD_{i,d}}$ where $R_{i,d}$ is the return of stock i on day

[25] http://boyer.byu.edu/Research/skewdata2.html

d and $VOLD_{i,d}$ is the dollar volume of stock i traded on day d. We multiply $ILLIQ_i$ with 10^6 (except Table 1 where we multiply it with 10^8).

Maximum daily return (MAX): The largest daily return of a stock during the previous month.

Minimum daily return (MIN): The minimum daily return of a stock during the previous month.

Mispricing measure (MISP): We use the Stambaugh, Yu and Yuan (2015) mispricing measure which is constructed by combining rankings on 11 anomaly variables. We obtain MISP data from Robert Stambaugh's website.[26]

Momentum (MOM): Momentum is the compounded return from month $t-12$ to month $t-2$.

Profitability (PROFIT): Following Fama and French (2015), we define a firm's profitability as annual revenues minus costs of goods sold, interest expense and selling, general and administrative expenses, all divided by book equity, pairing data as in their paper.

Reversal (REV): Reversal is the return in the previous month $t-1$.

SCORE: At the end of each month t we rank VOL, SKEW and KURT cross-sectionally in ascending order with VOL and KURT multiplied by -1, so that all distribution shape parameters are ranked according to moment preferences, that is, $r_{VOL_{i,t}} = rank(-VOL_{i,t})$, $r_{SKEW_{i,t}} = rank(SKEW_{i,t})$ and $r_{KURT_{i,t}} = rank(-KURT_{i,t})$. We then standardize each rank as follows: $z_M = (r_M - \overline{r_M})/\sigma_{r_M}$, where $M =$

[26] http://finance.wharton.upenn.edu/~stambaug/

$\{VOL_{i,t}, SKEW_{i,t}, KURT_{i,t}\}$, $\overline{r_M}$ is the rank cross-sectional sample mean and σ_{r_M} is the rank cross-sectional standard deviation. Finally, we compute SCORE for each stock i as the mean of the previously calculated individual z-scores, i.e., $SCORE_{i,t} = (1/3)\left(z_{VOL_{i,t}} + z_{SKEW_{i,t}} + z_{KURT_{i,t}}\right)$.

SIZE: Firm size is the log of the market value of equity in millions of dollars, that is, the number of shares outstanding times the price of the stock.

Appendix B

The formulas of the second, third and fourth-order non-central moments of the future log-return distribution implied from option prices are given as follows (see Bakshi, Kapadia and Madan (2003)):

$$V_{i,t} = e^{r\tau}\left(\int_{S_{i,t}}^{\infty} \frac{2\left(1-\ln\left[\frac{K}{S_{i,t}}\right]\right)}{K^2} C_{i,t}(\tau,K)dK + \int_{0}^{S_{i,t}} \frac{2\left(1+\ln\left(\left[\frac{S_{i,t}}{K}\right]\right)\right)}{K^2} P_{i,t}(\tau,K)dK\right) \tag{B.1}$$

$$W_{i,t} = e^{r\tau}\left(\int_{S_{i,t}}^{\infty} \frac{6\ln\left[\frac{K}{S_{i,t}}\right]-3\left(\ln\left[\frac{K}{S_{i,t}}\right]\right)^2}{K^2} C_{i,t}(\tau,K)dK - \int_{0}^{S_{i,t}} \frac{6\ln\left[\frac{S_{i,t}}{K}\right]+3\left(\ln\left[\frac{S_{i,t}}{K}\right]\right)^2}{K^2} P_{i,t}(\tau,K)dK\right) \tag{B.2}$$

$$X_{i,t} = e^{r\tau}\left(\int_{S_{i,t}}^{\infty} \frac{12\left(\ln\left[\frac{K}{S_{i,t}}\right]\right)^2-4\left(\ln\left[\frac{K}{S_{i,t}}\right]\right)^3}{K^2} C_{i,t}(\tau,K)dK + \int_{0}^{S_{i,t}} \frac{12\left(\ln\left[\frac{S_{i,t}}{K}\right]\right)^2+4\left(\ln\left[\frac{S_{i,t}}{K}\right]\right)^3}{K^2} P_{i,t}(\tau,K)dK\right) \tag{B.3}$$

,

respectively. $C_{i,t}(\tau,K)$ ($P_{i,t}(\tau,K)$) denotes the call (put) option price of stock i at time t with strike price K and time-to-maturity τ (which is equal to 1 month). $S_{i,t}$ is stock price of stock i at time t adjusted for future dividends. In particular, we subtract from the current stock price the present value of future dividends with ex-dividend dates during the following month, as in Bali, Hu and Murray (2017). r denotes the risk-free rate.

In order to calculate the integrals inside the previous formulas we interpolate implied volatilities between the lowest and highest available moneyness using cubic splines and perform constant extrapolation with 1% and 300% moneyness as bounds, resulting in 1,000 grid points. Subsequently, we convert implied volatilities to option prices using the Black-Scholes formula and use those prices to numerically calculate the above integrals.

The first non-central moment can be approximated using higher-order moments as:

$$\mu_{i,t} = e^{r\tau} - 1 - \frac{1}{2}V_{i,t} - \frac{1}{6}W_{i,t} - \frac{1}{24}X_{i,t} \tag{B.4}$$

Using these option-implied moments we compute the volatility (VOL), skewness (SKEW) and kurtosis (KURT) of the 1-month ahead return distribution for stock i at the end of each month t as follows:

$$VOL_{i,t} = \sqrt{V_{i,t} - \mu_{i,t}^2}, \tag{B.5}$$

$$SKEW_{i,t} = \frac{W_{i,t} - 3\mu_{i,t}V_{i,t} + 2\mu_{i,t}^3}{VOL_{i,t}^3} \tag{B.6}$$

$$KURT_{i,t} = \frac{X_{i,t} - 4\mu_{i,t}W_{i,t} + 6\mu_{i,t}^2V_{i,t} - 3\mu_{i,t}^4}{VOL_{i,t}^4}. \tag{B.7}$$

Appendix C

Table C1: Long term performance of SCORE portfolios

Decile portfolios are formed every month from January 1996 to April 2016 by sorting stocks based on the end-of-month SCORE measure. Low decile portfolio includes stocks with the lowest SCORE (bad) and high decile portfolio includes stocks with the highest SCORE (good). The table reports average returns and alphas of the Fama and French (2015) 5-factor model (FF5) over months t+2 up to t+6. Panel A shows value-weighted returns and Panel B shows equally-weighted returns. The t-statistics (in parentheses) are computed using Newey-West (1987) standard errors with 5 lags.

	t+2			t+3			t+4			t+5			t+6		
	Bad	Good	GMB	Bad	Good	GMB	Bad	Good	GMB	Bad	Good	GMB	Bad	Good	GMB
Panel A: Value-weighted															
Raw	0.33	1.03	0.71	0.42	1.08	0.66	0.37	0.87	0.50	0.23	0.90	0.67	0.47	1.01	0.54
	(0.70)	(3.44)	(2.43)	(0.86)	(3.71)	(2.05)	(0.76)	(3.00)	(1.56)	(0.45)	(2.98)	(2.00)	(0.89)	(3.28)	(1.63)
FF5	-0.51	0.01	0.52	-0.47	0.07	0.55	-0.43	-0.09	0.34	-0.52	-0.03	0.49	-0.32	0.09	0.41
	(-2.79)	(0.05)	(2.24)	(-2.49)	(0.53)	(2.44)	(-2.69)	(-0.73)	(1.57)	(-2.81)	(-0.21)	(1.95)	(-1.38)	(0.68)	(1.62)
Panel B: Equally-weighted															
Raw	0.58	1.03	0.44	0.69	1.11	0.42	0.62	1.03	0.41	0.69	1.11	0.42	0.90	1.09	0.19
	(1.48)	(2.98)	(2.87)	(1.68)	(3.16)	(2.39)	(1.45)	(2.93)	(2.50)	(1.61)	(3.12)	(2.39)	(2.06)	(3.14)	(1.10)
FF5	-0.45	-0.05	0.40	-0.31	0.04	0.35	-0.33	-0.02	0.32	-0.21	0.08	0.29	-0.06	0.07	0.13
	(-4.47)	(-0.43)	(3.00)	(-2.37)	(0.36)	(2.48)	(-2.90)	(-0.14)	(2.41)	(-1.15)	(0.68)	(1.52)	(-0.31)	(0.65)	(0.69)

Appendix D

***ANNBETA*:** Following Barth and So (2014), announcement beta is the estimate of coefficient β_3 from the following firm-level regression model:

$$xr_{i,t} = \alpha_i + \beta_{1,i}MKT_t + \beta_{2,i}AnnDay_{i,t} + \beta_{3,i}\left(MKT_t * AnnDay_{i,t}\right) + \varepsilon_{i,t}, \quad \text{(D.1)}$$

where $xr_{i,t}$ is the excess daily return of firm *i* on day *t*, MKT denotes the excess market return, and $AnnDay_{i,t}$ is a dummy variable that takes the value 1 on trading days {*d-1*, *d*, *d+1*}, where *d* is the EAD, and 0 otherwise. We estimate this model using daily data during the past 12 quarters. We require at least 8 EADs and at least 451 observations.

ATMIV: The average of the annualized call implied volatility with delta=0.5 and the annualized put implied volatility with delta=-0.5. Annualized implied volatilities are sourced from the 10-day Volatility Surface File of OptionMetrics.

B/M: The ratio of firm book value of equity (CEQ) to market capitalization. Market capitalization is defined as the product of share price (PRC) times the number of shares outstanding (SHROUT). We drop observations with negative book value. We use the *B/M* ratio computed at the end of the previous fiscal quarter.

BETA: The market beta estimated from the Fama-French-Carhart 4-factor (FFC4) regression model specified in equation (3). We estimate this model at *t* using daily data from *t*-250 to *t*-25 and requiring at least 200 observations. *MKT*, *SMB*, *HML*, and *WML* returns are sourced from Kenneth French's online data library.

DISPERSION: The standard deviation of the earnings per share (EPS) forecasts for the next quarterly earnings announcement scaled by the absolute value of the mean EPS forecast. EPS forecasts are sourced from I/B/E/S.

IVOL: The firm-level annualized standard deviation of residuals from the FFC4 regression model specified in equation (3). We estimate this model at *t* using daily data from *t*-250 to *t*-25 and requiring at least 200 observations.

LEVERAGE: The ratio of total liabilities (LT) to the sum of market capitalization and total liabilities. Market capitalization is defined as the product of share price (PRC) times the number of shares outstanding (SHROUT). We use the *LEVERAGE* ratio computed at the end of the previous fiscal quarter.

***LN(PRICE)*:** The natural logarithm of the share price (PRC).

LN(SIZE): The natural logarithm of the firm's market capitalization (in million $). Market capitalization is defined as the product of share price (PRC) times the number of shares outstanding (SHROUT). We use the market capitalization computed at the end of the previous fiscal quarter.

MOM: The cumulative stock return from day *t*-250 to day *t*-25. We require at least 200 daily observations.

***NUMEST*:** The number of analysts providing EPS forecasts for the next quarterly earnings announcement sourced from I/B/E/S.

O/S: The ratio of daily option trading volume to daily stock trading volume. Option trading volume is multiplied by 100, as each option contract corresponds to a 100-share lot. We sum up the trading volume of all call and put options with the same expiry as the one used to define the indicator *CONCAVE*.

RVIV: The difference between the annualized realized (historical) volatility and the at-the-money implied volatility (*ATMIV*). Realized volatility is sourced from the 10-day Historical Volatility File provided by OptionMetrics.

RUNUP: The cumulative stock return from day *t*-4 to day *t*. We require all 5 daily observations.

RNK: The Risk-Neutral Kurtosis computed as per the definition of Bakshi et al. (2003). We use prices of OTM and ATM options with the same expiry as the one used to define the indicator *CONCAVE*. We require at least 4 options, with at least 2 calls and 2 puts. Option prices are converted to implied volatilities and vice versa via the Black-Scholes formula. We use a cubic spline to interpolate implied volatilities between the lowest and the highest available strikes and perform a constant extrapolation outside this range, with lower bound *K/S*=1/3 and upper bound *K/S*=3.

RNS: The Risk-Neutral Skewness computed as per the definition of Bakshi et al. (2003). We use prices of OTM and ATM options with the same expiry as the one used to define the indicator *CONCAVE*. We require at least 4 options, with at least 2 calls and 2 puts. Option prices are converted to implied volatilities and vice versa via the Black-Scholes formula. We use a cubic spline to interpolate implied volatilities between the lowest and the highest available strikes and perform a constant extrapolation outside this range, with lower bound *K/S*=1/3 and upper bound *K/S*=3.

STOCKTR: The ratio of daily stock trading volume (VOL) to shares outstanding (SHROUT*1,000).

TSIV: The term structure estimator of ATM implied volatility proposed by Dubinsky et al. (2019) and defined as the square root of the following expression:

$$\left(\sigma_{i,term}^{Q}\right)^2 = \frac{\sigma_{t,T_1}^2 - \sigma_{t,T_2}^2}{T_1^{-1} - T_2^{-1}}, \tag{D.2}$$

where σ_{t,T_1}^2 is the squared annualized ATM implied volatility corresponding to the nearest expiry T_1, whereas σ_{t,T_2}^2 is the squared annualized ATM implied volatility corresponding to the second nearest expiry T_2. T_1 is the same as the maturity of the options used to define the indicator *CONCAVE*. We use the nearest-to-the-money option to compute the ATM implied volatility, with moneyness defined as the strike price divided by the forward price. *TSIV* is not defined when $\sigma_{t,T_1}^2 < \sigma_{t,T_2}^2$.