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Option Characteristics as Cross-Sectional Predictors*

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Abstract

We provide the first comprehensive analysis of option information for pricing the cross-section of stock returns by jointly examining extensive sets of firm and option characteristics. Using portfolio sorts and high-dimensional methods, we show that certain option measures have significant predictive power, even after controlling for firm characteristics, earning a Fama-French three-factor alpha in excess of 20% per annum. Our analysis further reveals that the strongest option characteristics are associated with information about asset mispricing and future tail return realizations. Our findings are consistent with models of informed trading and limits to arbitrage.

Keywords: Asset Pricing, Factor Models, High-dimensional Methods, Option Characteristics.

JEL classification: C13, C14, G11, G12, G14

1 Introduction

A central question in finance is to understand why average returns differ across assets. Economic theory stipulates that differences in expected return should reflect different exposures to systematic risk. In the capital arbitrage pricing model (CAPM) of Sharpe (1964) and Lintner (1965), risk is measured as the covariance between individual stock and market returns. Since then, researchers in empirical asset pricing have documented a plethora of seemingly new variables, or factors, that predict returns in the cross-section and are simultaneously not explained by the CAPM or more advanced benchmark risk models such as the Fama & French (1993) three-factor one. Cochrane (2011) labels this the "multidimensional challenge" and calls for new methods to determine which of these variables actually provide incremental information and are, thus, non-redundant. Inspired by Cochrane's presidential address, recent studies provide comprehensive analyses of this matter using modern (and sophisticated) statistical and econometric methods; see, e.g., Freyberger, Neuhierl & Weber (2020), Feng, Giglio & Xiu (2020), Gu, Kelly & Xiu (2020), Kozak, Nagel & Santosh (2020), Bali, Beckmeyer, Moerke & Weigert (2021), Bakalli, Guerrier & Scaillet (2021), Chaieb, Lanlois & Scaillet (2021) and the textbook treatment in Nagel (2021). While this literature agrees that only few characteristics provide significant and independent information, their analyses are limited to the space of firm characteristics; see also the review Hou, Xue & Zhang (2020).

On the other hand, findings from a large literature on index option pricing indicate that price jumps render markets for the underlying assets incomplete and that options are non-redundant. Moreover, it documents that a substantial part of aggregate equity premium is related to jump risk (e.g., Andersen, Fusari & Todorov (2015)), and that this premium is effectively impossible to identify from historical returns alone. A complementary literature argues that option markets provide an interesting trading avenue for investors seeking to exploit their informational advantage, providing them with embedded leverage (Black 1975) as well as allowing them to obtain better liquidity or to hide their information more effectively, e.g., Back (1993), Biais & Hillion (1994), Easley, O'hara & Srinivas (1998) and An, Ang, Bali & Cakici (2014). Taken together, these lines of research suggest that important forward-looking information can be extracted from individual equity options, that options-based measures should be not be subsumed by common proxies for risk such as the usual factor loadings or firm characteristics, and that option information may utilized to improve our understanding of the drivers and pricing of the cross-section of stock returns. Consistent with this interpretation, Bali & Hovakimian (2009) and Bali, Hu & Murray (2019), among others, find that certain *option characteristics* appear priced in the cross-section. However, foreshadowing a subset of our results below, we demonstrate that their pricing effects disappear when replacing standard benchmark factor models with controls based on an extensive set of firm characteristics. Hence, it remains an open question whether option characteristics provide significant information about the cross-section of stock returns.

In this paper, we answer this question by examining the information embedded in an exhaustive set of option characteristics, while simultaneously controlling for an extensive set of firm characteristics to avoid the "multidimensional" critique. Importantly, we uncover that some option characteristics, indeed, provide significant and non-redundant information about the cross-section.

Specifically, our analysis provides new and interesting perspectives on cross-sectional asset pricing, option pricing for individual equities and factor models of asset returns. First, we confirm that portfolio sorts using most existing option characteristics, indeed, generate economically large – and statistically significant – alphas when assessed against several standard factor models. For example, the magnitude can be as large as 20% per annum when assessed against the Fama-French three-factor model. Second, when "the bar is raised" and the option characteristics are confronted with more advanced factor models or statistical factors estimated using information available under the physical probability measure, we show that most alphas shrink dramatically in magnitude and become statistically insignificant. However, a few remain important. In particular, when restricting attention to alternative linear factor models, we demonstrate that only 5 out of 17 option characteristics provide significant information, after controlling for a large set of firm characteristics. Third, we expand on the linear factor analysis using modern methods from high-dimensional statistics. Specifically, when we *jointly* control for a large number of known cross-sectional predictors in addition to the option characteristics in an adaptive group LASSO setting, thereby allowing for substantial nonlinearity in the predictive relation, we "knock out" one additional option characteristic. The LASSO analysis further shows that most of the predictive power arises from small (low rank) and large (high rank) values of the option characteristics, corresponding to the usual low (one) and high (ten) portfolios in decile sorts. This is consistent with the "rank effect" (e.g., Hartzmark (2015)). Consequently, we provide rigorous evidence showing that only 4 out of 17 option characteristics provide incremental information about future stock returns and that this information arises mainly from "extreme" realizations of the predictors. The four significant and economically important characteristics are related as they all speak to the shape of the implied volatility (IV) smirk, albeit with different construction.

Fourth, we systematically examine the sources of predictability in the four successful characteristics through the lens of a flexible class of option pricing models. Naturally, this involves going beyond the Black-Scholes-Merton (BSM) setting since we seek to understand the role of important features such as tail risk, leverage effects and stochastic volatility. In the spirit of Andersen, Fusari & Todorov (2017) and Bandi, Fusari & Reno (2019), we refer to this as a "structural analysis". Specifically, since most option pricing models attribute variation in the IV surface to a small set of risk factors, we utilize IV surface expansions to derive testable implications for the four characteristics and use nonparametric econometrics to estimate the relevant risk factors, thereby facilitating an empirical decomposition of the information embedded in the predictors. The main advantages of relying on such expansions rather than estimating parametric option pricing models are twofold. One, they are valid for a general class of models, making the empirical analysis less subject to parametric misspecification when recovering the "structural" risk factors. Two, they are often much faster and much simpler to compute in practice. Our analysis shows that the risk factors derived from these expansions, indeed, carry significant explanatory power for the four option characteristics, especially the factors related to the left-jump intensity, leverage effect and spot volatility. Moreover, if we combine these risk factors with firm characteristics and the max statistic by Bali, Cakici & Whitelaw (2011), which reflects asset (over-)valuation, this span (almost) all of the variation in the significant option characteristics. Importantly, however, we find that the signs of the cross-sectional risk premia associated with the left-jump intensity, leverage effect and spot volatility are *not* consistent with a risk compensation explanation, unlike the typical conclusions obtained in the equity index option pricing literature. In fact, we show that an elevated intensity of left-tail jumps predicts future negative realizations of returns for the underlying assets. Hence, this structural, IV expansion-based, analysis shows that the option characteristics provide incremental information about asset mispricing, overvaluation and future tail return realizations, consistent with models of informed trading and frictions in option markets, such as the demand-based option pricing model of Garleanu, Pedersen & Poteshman (2008).

Fifth, we take a deep dive into asset overvaluation and limits to arbitrage, possible channels to explain the predictive information in the option characteristics, using conditional double sorts. Specifically, we use the Stambaugh, Yu & Yuan (2015) mispricing score to indicate overvaluation as well as the Corwin & Schultz (2012) liquidity measure and idiosyncratic volatility as two proxies for trading frictions; see, e.g., Wurgler & Zhuravskaya (2002) and Stilger, Kostakis & Poon (2017). The double sorts reveal that the successful option predictors, indeed, carry information about asset overvaluation, confirming the findings from our structural analysis, and that parts of the return spread is not realizable by investors due to trading frictions. However, the return spreads remain large and significant for the stocks that are deemed fairly valued and feasible to trade.

Finally, we explore possible limits to arbitrage in a greater detail. We restrict the analysis to the S&P 500 universe, carry out portfolio sorts using the option characteristics and employ our most challenging set of controls. We show that the successful option characteristics no longer generate significant alpha despite delivering large Sharpe ratios. Moreover, the left-jump intensity and the leverage effect are the most important explanatory variables. Hence, by combining all the empirical results, our analysis suggests that the successful option characteristics, those that are unspanned by firm characteristics and risk factors, provide information about asset mispricing, overvaluation and future tail return realizations. However, the mispriced assets may be subject to trading frictions and, thus, may not be exploitable. Still, the predictors embed important valuation and tail information.

Our findings have a number of implications for research in empirical asset pricing. Specifically, we confirm that option markets contain valuable information for estimating the expected return on individual equities. However, our analysis also demonstrates that significant "alphas" obtained from standard low-dimensional factor models are not necessarily evidence of anomalous behavior, as previous research has claimed. Most option characteristics fail to survive our extensive sets of controls. The few successful characteristics are those associated with the shape of the IV smirk. Moreover, our structural analysis suggests that the information embedded in the successful characteristics are associated with asset mispricing, overvaluation, future tail return realizations and is subject to arbitrage limits. In contrast with the equity index option pricing literature, standard risk factors such as volatility and jump risk do not appear to be priced in the cross-section of stock returns.

The rest of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides an empirical examination of option characteristics as cross-sectional stock return predictors. Section 4 explores the information in the successful option characteristics using structural IV expansions. Section 5 further examines overvaluation and limits to arbitrage as potential channels of predictability, and Section 6 concludes. Appendices A and B provide additional implementation details and empirical results, respectively.

2 Related Literature

It has long been recognized that derivative prices provide an interesting lens to uncover rich information about the underlying assets, economic states and associated risks. Specifically, since the early contributions by Breeden & Litzenberger (1978) and Banz & Miller (1978), much progress has been made to uncover important information about economic states from option prices. Indeed, Ross (2015) and Borovička, Hansen & Scheinkman (2016), among others, study conditions under which the entire physical distribution of asset returns can be recovered from their option surface. While these conditions appear rather restrictive, consensus has emerged that interesting quantities, often related to economic risks, can be estimated from option prices; see, e.g., Andersen et al. (2015), who study equity risk premia embedded in index option, or Dew-Becker & Giglio (2020), who estimate cross-sectional uncertainty from option prices and study its relationship to future economic activity. Given these important and successful inquiries at the aggregate level, it appears natural to systematically and comprehensively investigate the cross-sectional predictive content in option prices.

It is, however, surprising that a large scale study that examines the information embedded in option prices for the cross-section of stock returns *jointly* with a large number of known cross-sectional predictors has not been undertaken, for at least two reasons. First, option prices are inherently forward-looking and may, thus, provide valuable information relative to other firm characteristics, which almost exclusively depend on past realization of returns, trading volume and accounting variables. Second, stocks that have listed options are on average larger firms. Hence, this automatically excludes microcaps, which often limit the interpretability of many anomaly studies. Existing studies usually construct a few option characteristics as predictors and typically only control for a very small set of firm characteristics, or factors, when assessing whether they contain incremental information. Naturally, this casts doubt on associated interpretations that option prices, e.g., reveal mispricing among assets, informed trading in option markets or the existence of some new risk factor(s). In contrast, inspired by the many papers below, we adopt a large scale study to examine the predictive information in option-implied variables, which are collectively dubbed *option characteristics*.

Many option-implied predictors build on a potential risk-reward relationship between the variance risk-premium (VRP) and subsequent stock returns; see, e.g. Bali & Hovakimian (2009), who propose cross-sectional return predictor inspired by related work at the index level in Coval & Shumway (2001) and Bakshi & Kapadia (2003). Similarly, Kilic & Shaliastovich (2019) demonstrate that good (upside) and bad (downside) VRP on the aggregate stock market have complementary predictive power and require differential pricing for aggregate returns, portfolios of returns (the usual size, book-to-market, etc.), and returns on corporate bonds, that is, on high-yield and investment grade. These results are corroborated by Feunou, Jahan-Parvar & Okou (2018) for aggregate returns, and by Feunou, Aliouchkin, Tedongap & Xu (2019), Tang (2019), Pederzoli (2020) and Duarte, Jones & Wang (2022) for the cross-section of stocks, who all document strong predictive power of related option characteristics, which is unspanned by standard measures of crash risk.

Several other papers propose measures from the option surface that are related the shape of the implied volatility smirk or corresponding risk-neutral skewness portfolios; see, e.g., Xing, Zhang & Zhao (2010), Yan (2011), Conrad, Dittmar & Ghysels (2013), Stilger et al. (2017), Jones, Mo & Wang (2018) and Bali et al. (2019). In particular, they construct different measures in different empirical settings, which generate opposite pricing results. For example, Conrad et al. (2013) document a negative relation between ex-ante risk-neutral skewness and asset returns, while Stilger et al. (2017) find a positive relation. Therefore, associated explanations for the skewness predictability results similarly vary from risk compensation to informed trading, limits to arbitrage and asset mispricing. Most importantly, however, as for the physical distribution, e.g. Jiang, Wu, Zhou & Zhu (2020), measures of asymmetry of the return distribution comprise strong predictors of future returns.

Motivated by the work of Back (1993) and Easley et al. (1998) on informed trading, Cremers & Weinbaum (2010) use deviations from put-call parity to predict stock returns, arguing that their significant results are due to mispricing of the underlying assets. Moreover, An et al. (2014) generalize their analysis by applying the (unrestricted) level and changes of call and put IV to predict stock returns, obtaining significant results while controlling for VRP, risk-neutral skewness as well as put-call deviations. They argue that their results are consistent with a noisy rational expectation model of informed trading. Consistent with these findings and interpretations, Johnson & So (2012) show that the ratio of the volume between options and stocks predicts weekly returns. Moreover, Collin-Dufresne, Fos & Muravyev (2020) provide evidence of informed trading in the option markets around corporate events, and Chordia, Kurov, Muravyev & Subrahmanyam (2020) reach a similar conclusion when examining the (signed) order flow in equity index options. Bali & Murray (2019) combine a subset of these option characteristics to develop a factor model for optionable stocks.

Another strand of literature aims to extract measures of systematic risk from the option surface. This literature largely works at the aggregate level, that is, with index options rather than individual options. Notable contributions include Kozhan, Neuberger & Schneider (2013) and Schneider & Trojani (2019), who analyze trading of aggregate skewness from equity index options, demonstrating that this is associated with a large risk premium related to volatility. Orlowski, Schneider & Trojani (2020) study the trading of the jump component of skewness and find that this is significant. Relatedly, building on the work of Martin (2017), Martin & Wagner (2019) and Kadan & Tang (2020) derive option-based lower bounds on the equity premium for individual stocks and show that the bounds vary with key firm characteristics such as its beta, book-to-market ratio, size and momentum, and that they provide useful information about future returns.

Inspired by the work on index options, Cremers, Halling & Weinbaum (2015) study the the pricing of aggregate jump and volatility risk in the cross-section of stock returns. Specifically, they measure jump and volatility risk using portfolios of at-the-money (ATM) straddles for different maturities, which are constructed to be "beta" neutral, with a weighting scheme derived from their respective open interest. These straddles isolate vega and gamma as proxies for volatility and jump risk, respectively, and are shown to carry a significant risk premium in the cross-section. Related findings are made by Gourier (2016), Lin & Todorov (2019), Begin, Dorion & Gauthier (2020) and Han, Liu & Tang (2020). Besides volatility and jump risk, Baltussen, Van Bekkum & Van Der Grient (2018) show that the volatility of implied volatility carries significant predictive power for stock returns.

It is important to note that measures derived from option prices such as implied volatility, skewness or a jump intensity (almost always) reflect properties of the risk-neutral distribution. In most instances, related measures can be computed under the physical distribution. Hence, in order to understand the incremental information in some characteristic derived from option prices, it is important to control for the corresponding "physical" quantity. Without being exhaustive, we highlight some important contributions in this realm. Ang, Hodrick, Xing & Zhang (2006) show that stocks with high idiosyncratic volatility earn abnormally small return. Harvey & Siddique (2000), Boyer, Mitton & Vorking (2010), Amaya, Christoffersen, Jacobs & Vasquez (2015) and Schneider, Wagner & Zechner (2020) estimate (co-)skewness from historical data, thus under the physical distribution, and study its pricing implications. The study of skewness and its pricing is closely related to the study of downside risk. Bali et al. (2011) find that investors have lottery preferences and are willing to earn lower returns for holding stocks that offer a small likelihood of very high returns, consistent with cumulative prospect theory (e.g., Barberis & Huang (2008)), and may be interpreted as measure of asset (over-)valuation. Kelly & Jiang (2014) construct a time-varying tail measure from the cross-section and show that tail risk is significantly priced. Ang, Chen & Xing (2006) and Lettau, Maggiori & Weber (2014) study (conditional) downside market risk and document its importance for explaining the returns within and across asset classes. Finally, Neuhierl & Varneskov (2021) show that a low-frequency risk factor, which reflects exposure to persistent economic shocks such as disasters, commands a large risk premium.

3 Empirical Evaluation of Option Characteristics

This section describes the data, the construction of option characteristics and a large set of associated firm characteristics. Furthermore, we analyze predictability from two different perspectives. First, we rely on standard portfolio sorts and assess significance of the risk-adjusted returns from long-short strategies (alphas) using a substantially more challenging set of control variables and factor models than typically employed in the literature, thus raising the bar for significance. Portfolio sorts provide a simple, yet powerful out-of-sample perspective on predictability. This is important as Martin & Nagel (2021) show that spurious in-sample predictability can arise if the dimension of the predictor set is of the same order as the sample size. Second, we assess the forecasting prowess of the option characteristics for excess stock returns *jointly* with a large set of firm characteristics using the adaptive group LASSO procedure of Freyberger et al. (2020). This accommodates nonlinearity in the predictive relation and, thus, allows us to assess where in the characteristic distribution predictability arises.

3.1 Data Collection

We obtain data from the following sources. First, we collect implied volatility (IV) observations from the *standardized* IV surface in OptionMetrics, along with associated option and strike prices as well as the raw (actual) option trading volumes. Second, stock prices, trading volumes and returns are from the Center for Research in Securities Prices (CRSP). Finally, firm fundamentals are obtained from Compustat. We use the same 62 firm (normalized) characteristics as in Freyberger et al. (2020), which comprise a large and representative set of stock characteristics from the literature.

3.2 Option Characteristics

Motivated by the extensive literature in Section 2, we construct a comprehensive set of option characteristics. To this end, we have followed the respective papers' implementations closely, albeit with slight modifications in some cases to have a unified framework for analyzing return predictability. Specifically, we construct a *monthly* dataset from 1996 through 2018, since OptionMetrics data starts in 1996. Before proceeding, it is important to note that the option-stock volume variable is the only option characteristic that does not rely on standardized IV surface data, but rather relies on the actual traded volumes. The remaining option characteristics use the standardized implied volatility surface provided by OptionMetrics, which, as highlighted by, e.g., An et al. (2014), circumvents the need to make arbitrary choices of strikes and maturities in the construction.

- Call and put IV (`CIV` and `PIV`, respectively) and changes therein (Δ`CIV` and Δ`PIV`). Following An et al. (2014), we use a maturity of exactly 30 days and a delta of 0.50 (and -0.50 for puts).
- The option-stock volume ratio (`O/S`). We follow Johnson & So (2012) and use options with maturities between 5 and 30 days, and compute their monthly volume (multiplied by 100 since each contract has a 100-stock lot size). `O/S` is, then, log(stock volume/option volume).
- The variance risk premium ($\texttt{VRP} = \texttt{IV} - \texttt{RV}$), where `IV` is computed using model-free implied variance (Carr & Madan 1998), and `RV` is the rolling 20-day sum of squared returns (annualized). This is standard in the literature, e.g., Bakshi & Kapadia (2003) and Carr & Wu (2009).
- Implied volatility spreads, which are computed as the difference between put and call IV with a maturity of 30 days, thus capturing information about the magnitude of the IV smirk (or smile). The first spread is constructed near at-the-money (ATM) using 0.50 delta call options

and -0.50 delta put options (labeled, $\texttt{IVS}_{\text{ATM}}$). Similarly, the second is constructed out-of-the-money (OTM) with 0.50 delta call options and -0.20 delta put options ($\texttt{IVS}_{\text{OTM}}$). The two variables are in line with Xing et al. (2010) and Yan (2011).

- Risk-neutral skewness (`SKEW`), similarly to IV spreads, use the difference between average put and average call IV. Again, we use options with a maturity of exactly 30 days and the averages are computed across a range of deltas from 0.20 to 0.40 for calls and -0.40 to -0.20 for puts.

- β_{Jump} and β_{Vol} are the stock-specific betas with respect to S&P 500 gamma and vega option portfolios. Following Coval & Shumway (2001) and Cremers et al. (2015), we construct two straddle portfolios with 0.50 delta for calls (-0.50 for puts) and maturities of 30 and 60 days. These portfolios are made beta-neutral using the option-implied betas by the Black-Scholes model, assuming that the beta of the underlying (S&P 500) is one. The vega and gamma portfolios are constructed as linear combinations of the beta-neutral straddles, rebalanced daily to maintain gamma and vega. Finally, we estimate the stock-specific betas with respect to these risk factors as the regressions slopes using daily returns and a rolling 250-day window.[1]

- Risk-neutral variance measures. Inspired by Kadan & Tang (2020) and Tang (2019), we construct estimates of risk-neutral variance by calculating the measure for each available maturity, annualizing and taking the average. Specifically, $\texttt{VAR}^{\mathbb{Q}}$ is the risk-neutral (Carr & Madan 1998) variance, $\texttt{VAR}^{+}$ and $\texttt{VAR}^{-}$ denotes the corresponding positive (call) and negative (put) semi-variance, and $\texttt{AVAR} = \texttt{VAR}^{-} - \texttt{VAR}^{+}$ estimates the variance asymmetry.

- `KT` is a model-free measure of expected stock returns based on risk-neutral variances, developed by Kadan & Tang (2020). It differs subtly from $\texttt{VAR}^{\mathbb{Q}}$ by the approximation of the risk-neutral integral and from the corresponding measure in Martin & Wagner (2019) by applying to the full cross-section of stocks. The latter has the S&P 500 as a reference universe.[2]

- Volatility-of-volatility is first computed for call and put options ($\texttt{VOV}_{\text{call}}$ and $\texttt{VOV}_{\text{put}}$). Specifically, following Baltussen et al. (2018), we use options with a maturity of 30 days and deltas of 0.50 for calls (-0.50 for puts). Each month, we compute the time series mean and standard deviation of call and put IV separately. Volatility-of-volatility is, then, the standard deviation divided by its mean. Finally, our aggregate measure, `VOV`, is the average of $\texttt{VOV}_{\text{call}}$ and $\texttt{VOV}_{\text{put}}$.

This amounts to 17 option characteristics. Some of these require more extensive data usage than others, implying that there is not always sufficient option data available to construct every characteristics for all stocks. Hence, our empirical analysis is based on unbalanced panels of monthly observations.

[1] Note that, as in Cremers et al. (2015), we also include lagged market returns and lagged jump/volatility portfolio returns in the regression model and, accordingly, sum the coefficients (cf., their equation (3) on page 586).

[2] The risk-neutral variance measures are computed as integrals of weighted OTM option prices with respect to strike prices. To estimate them, we use discretized data and, following Kadan & Tang (2020), approximate the integrals from below by the minimum price at each interval; see their internet appendix for implementation details.

To underscore this feature, we illustrate the data coverage in Figure 1 for the CIV, ΔPIV, IVS_{ATM} and AVAR. Not surprisingly, since AVAR requires more extensive data to approximate its semi-variance integrals, the stock coverage is lower than for the three remaining predictors. Whereas the coverage is low early in the sample, it dramatically improves after 2005. Generally, while the stock coverage hovers around 10-20% of the investment universe in the beginning of the sample (1996), it fluctuates around 50% by the end, clearly illustrating a shift in the liquidity of stock options and their popularity among investors. When considering the coverage in terms of market equity, we observe that despite the number of included stocks being relative low in the first part of the sample, these represent more than 50% of the aggregate market equity. This fraction increases beyond 80% towards the end of the sample, clearly indicating that stock options are more prevalent among larger stocks.

Finally, we compute the correlations between the option characteristics in Figure 2. Interestingly, apart from a few (obvious) commonalities, most variables are only modestly correlated. Specifically, the CIV, PIV and VAR-based variables are, not surprisingly, highly correlated as they all depend on the level of volatility. Moreover, IVS_{ATM}, IVS_{OTM} and SKEW similarly exhibit high correlation as they capture features of the IV smirk, albeit at different deltas. Hence, it is interesting to examine whether the generally low correlation manifest itself as different predictive information.

3.3 Control Variables and Factor Models

We complement the 62 firm characteristics from Freyberger et al. (2020) by constructing a representative subset of forecasting variables that speak to the *physical* return distribution, cf. Section 2. This is important for, at least, two reasons. First, many of the option characteristics measure features of the *risk-neutral* return distribution such as the volatility level, volatility asymmetry and the probability of tail realizations.[3] Hence, to assess whether option characteristics, indeed, contain excess forecasting power for the cross-section, we need to include related measures that are derived from historical data.[4] Second, as these control variables also contain information about volatility risks (both level, upside and downside), tail risks, asset (over-)valuation and economic disasters, these may shed further light on why the literature has previously found option characteristics to be so successful.

Specifically, we include the downside beta (Ang, Chen & Xing 2006), the Kelly & Jiang (2014) tail beta, the realized skewness measure of Amaya et al. (2015) and the low-frequency market risk factor by Neuhierl & Varneskov (2021).[5] The first three measures are calculated using a rolling window of 250 daily observations, initialized when we have at least 60 days in the sample, and the low-frequency market factor is estimated using a rolling window of five years, requiring at least 2.5 years of data

[3] For example, Bollerslev, Tauchen & Zhou (2009) and Drechsler & Yaron (2011) argue that the VRP variable reflects volatility-of-volatility and tail risk, respectively; An et al. (2014) stipulate that CIV and PIV capture upside and downside volatility; similarly, AVAR may reflect the asymmetry between left and right-tail jumps or, more accurately, the risk-neutral expectation thereof, see, e.g., Patton & Sheppard (2015) and Bollerslev, Li, Patton & Quaedvlieg (2020).

[4] We will subsequently provide a structural decomposition of the successful option characteristics using implied volatility expansions in Section 4 to further examine what drives their excess predictive information.

[5] We found the average skewness measure by Jondeau, Zhang & Zhu (2019) to deliver results that are qualitative and quantitatively similar to those for realized skewness. Hence, the former is omitted for brevity.

to remain in the sample.[6] In addition, note that the volatility variables from Ang, Hodrick, Xing & Zhang (2006) and the max statistic (Bali et al. 2011) are already among the 62 characteristics.

In addition to these *physical* measures, we employ different factor models as controls in our portfolio sorting analysis. In particular, we consider the CAPM; the Fama & French (1992) three-factor model with and without the Carhart (1997) momentum factor (labeled FF3 and FF4, respectively); the Fama & French (2015) five-factor model with momentum (FF6); FF6 with either idiosyncratic volatility or the Pástor & Stambaugh (2003) liquidity factor (FF7a and FF7b); the Hou, Xue & Zhang (2015) investment model (HXZ); the HXZ augmented with the momentum factor (HXZM); and the mispricing factor model of Stambaugh & Yuan (2017), denoted by SY. Finally, based on portfolios constructed from the 62 firm characteristics in Freyberger et al. (2020), we use either the first five or ten principal components (PC5 and PC10) or the corresponding "risk premium" principal components (RP-PC5 and RP-PC10) based on the penalized estimator in Lettau & Pelger (2020a, 2020b).

These sets of controls raise the bar for significance considerably relative to the extant literature reviewed in Section 2, which typically employs the CAPM, FF3, FF4 and FF6.

3.4 Portfolio Sorts

Based on the option characteristics, we carry out a standard decile portfolio analysis and construct the usual "10-1" portfolios. Summary statistics of their return performance are provided in Table 1, which reveal several interesting observations. First, most option characteristics generate long-short portfolios with non-trivial returns and several exhibit strong investment performance.[7] Specifically, we observe that portfolios from 7 out of 17 characteristics deliver Sharpe ratios (SRs) above 0.50 in absolute magnitude, three above one, and one variable even delivers a SR above two. The best performing characteristics in terms of SR are the IV spread variables – $\mathtt{IVS}_{\mathrm{ATM}}$, $\mathtt{IVS}_{\mathrm{OTM}}$ and `SKEW` – as well as `AVAR`, which similarly captures the difference between put and call IV, albeit constructed differently. In addition, recall that the correlations between the option characteristics are relatively low and, as a result, a SR of 0.50 represents an interesting diversification opportunity for many investors.

Second, we observe distinct sign patterns for the expected returns on the long-short portfolios. Specifically, the volatility "level" variables deliver long-short portfolios with a negative return, showing that stocks with high IV tend to underperform stocks with low IV. Similarly, the IV spread characteristics (which is taken to include `AVAR`) deliver negative returns, demonstrating that stocks with the steepest IV smirks tend to perform worse than stocks with flatter IV smirks. Moreover, large changes in call IV predict higher returns on the underlying assets and, conversely, large changes in put IV predicts lower returns. Interestingly, using the stock-option volume predictor, we observe that stocks with high option volume relative to the volume of the underlying, i.e. low value of `O/S`, outperform stocks with a high ratio, as seen by the negative long-short portfolio return.

[6] Note that the market tail index from Kelly & Jiang (2014) can be calculated in real time from the available cross-section of stock returns. Once computed, we calculate rolling exposures to it as for the remaining control variables.

[7] The nomenclature "strong" signals both large positive and negative returns. We discuss the sign in detail below.

Third, the respective signs of the "1" *and* "10" portfolio returns are almost always positive; the exceptions are `PIV`, $\texttt{IVS}_{\text{ATM}}$ and `AVAR`, whose long portfolios exhibit negative returns that, however, are trivial compared to the magnitude of their respective short portfolios. This shows that the long-short portfolios with positive returns achieve this by the long leg out-sizing the return to the short leg, and vice versa for long-short portfolios with negative returns, suggesting that the option characteristics are able to identify average return differentials among (portfolios of) stock returns.

Finally, the risk-reward profiles differ considerably across long-short portfolios. For example, when sorting on the `CIV` and `PIV` measures, reflecting the volatility level, the resulting portfolios have high volatility ($\simeq 37\%$) and skewness with the opposite sign of the average returns. Hence, if reversing the long and short sides of the investment strategy, the properties mimic traditional equity investments, with associated downside risk. In contrast, portfolios based on the IV spreads have much lower volatility and skewness with the same sign as the returns. Hence, if the long and short side are reversed, these could possibly provide attractive investment opportunities.

3.5 Spanning Regressions

In addition to standard, unconditional risk-return and correlation statistics, we examine spanning regressions for the long-short portfolios based on the option characteristics using the challenging set of factor models described in Section 3.3. In particular, we explicate the regression estimates for the FF6 model in Table 2 and provide the alpha results for the remaining models in Table 3.

There are several interesting observations from Table 2. First, we observe that 9 out of 17 of the characteristics deliver portfolio returns with significant alpha at a 10% significance level (and 6 out of 17 at a 1% level). This is consistent with the literature in Section 2. Second, the exposures to risk factors for the volatility "level" variables are very similar; they display large positive exposures to `mktrf` and `smb` and large negative exposures to the remaining factors, and the factor model generates high adjusted R^2. However, only `PIV` delivers significant alpha (at a 10% level), consistent with models of downside risk. Third, the IV spread variables deliver large and significant alphas, with little exposure to the six risk factors and substantially lower adjusted R^2. Interestingly, while the risk factor exposures for `AVAR` are more in line with the volatility "level" variables, its alpha mimics those for the remaining IV spread variables. Fourth, $\Delta\texttt{CIV}$, $\Delta\texttt{PIV}$, `O/S` and β_{Vol} also deliver significant alpha. Whereas the `O/S` portfolio exhibits some factor exposure (to `hml`, `rmw` and `umd`), the returns for the remaining three characteristic portfolios are uncorrelated with the six risk factors.

The alpha results in Table 3 provide an elaborate overview of the performance of the 17 option characteristics. Specifically, and again consistent with prior literature, most portfolios deliver significant alpha for the CAPM, FF3 and FF4 controls. However, when the benchmark factor models increase in complexity, the number of significant characteristics drops. Whereas most appear significant in some spanning regressions and insignificant in others, there are five long-short portfolios that deliver significant alpha in all tests; the four IV spread variables and $\Delta\texttt{PIV}$, with the latter and `SKEW` being significant at a 10% level for the most stringent RP-PCA test. Moreover, despite the magnitudes of the alphas dropping in the PCA-based tests, in particular, they remain very large economically.[8] Interestingly, the PIV, ΔCIV, O/S and β_{Vol} variables lose significance once we employ PCA-based control variables, suggesting that their information is contained in the 62 firm characteristics. As a result, only 5 out of 17 option characteristics "survive" our first comprehensive test.[9]

3.6 Portfolio Sorting and $\mathbb{P}$-distribution Controls

We further stress the information embedded in the option characteristics by augmenting our challenging sets of control variables and models with four variables describing the *physical* ($\mathbb{P}$) return distribution; namely, downside risk, cross-sectional tail exposure, realized skewness and low-frequency market risk. Specifically, Table 4 provides results for the FF6 model augmented with the four $\mathbb{P}$-distribution controls and the max variable, reflecting asset overvaluation. To ease interpretation, we provide long-short portfolio results for the additional $\mathbb{P}$-controls in Table B.1 of Appendix B.

The results in Table 4 are broadly consistent with those in Table 2. However, there are some subtle, but important differences. First, the β_{Vol} long-short portfolio no longer generate significant alpha since it fully spanned by cross-sectional tail exposure and realized skewness risk. However, significance is now achieved by the VOV variable, albeit a 10% level. Second, for the remaining significant option characteristics in Table 2, the tail variables aid in explaining the variation, but does not subsume the alpha. Specifically, if restricting attention to the spanning regressions with significant alpha, we observe that at least one of the $\mathbb{P}$-distribution controls is significant, expect for ΔPIV.

Third, for IVS_{ATM}, IVS_{OTM} and SKEW, we find the downside risk, realized skewness and low-frequency market risk factors to enter significantly and more than double the adjusted R^2. Interestingly, if we combine the signs of the coefficient estimates in the risk factor spanning regressions with the signs of their respective risk premia in Table B.1, this shows that the realized skewness exacerbates the negative premia associated with the IV spreads, whereas the downside risk and low-frequency market risk factors partially explain them. However, despite embedding some information associated with downside risk, tail risk and economic disasters, the IV spreads clearly also embed different predictive information than these measures describing the *physical* return distribution.

Finally, the $\mathbb{P}$-distribution controls similarly enhances the explanatory power for PIV, ΔCIV, O/S and AVAR, leaving, however, significant alpha unexplained. Hence, this analysis corroborates the results of Tables 2 and 3, demonstrating that few option characteristics have strong predictive power for the cross-section, unspanned by an extensive set of factor models and control variables.

[8]Recall, a 1% alpha for monthly returns implies an annualized risk-adjusted return of 12%. This is very attractive for most investors, especially considering the modest factor exposure for the long-short portfolios in Table 2.

[9]Some option characteristics display non-monotonic significance patterns in the alphas as the complexity of the controls increases. For example, the VRP variable deliver insignificant alpha for all but the most complex PCA-based controls where the alpha turns negative despite providing positive excess returns in Table 1. We require that a given option characteristic must pass all control models to be deemed significant.

3.7 Characteristic Selection and Nonlinear Modeling of Returns

Our second significance test is based on stock return forecasting using the option characteristics *jointly* with a large set of firm characteristics. Specifically, to select which option characteristic contains incremental information, we use the adaptive group LASSO (henceforth, AG-LASSO) procedure, originally developed by Huang, Horowitz & Wei (2010) and examined in a finance context by Freyberger et al. (2020) and Bakalli et al. (2021). This analysis adds to the portfolio sorts in two ways. First, while portfolio sorts can be viewed as a "conditional" spanning exercise – conditioning on the option characteristics and subsequently implementing controls – the AG-LASSO agnostically selects the most important characteristics jointly and unconditionally. Second, the procedure accommodates nonlinearity in the predictive return relation, which allows us to assess which part of the option characteristic distribution contains predictive power, if the variable is deemed significant.

3.7.1 The Adaptive-Group LASSO Procedure

We briefly introduce the AG-LASSO procedure, referring to Freyberger et al. (2020) for a more elaborate discussion and implementation details. To this end, let $C_{s,i,t-1}$ denote the *rank-transformed* characteristic $s = 1, \ldots, S$ for a given asset i at time $t-1$. We are concerned with modeling excess returns, that is, with the predictive regression relation,

$$R_{i,t} = \sum_{s=1}^{S} m_{t,s}(C_{s,i,t-1}) + \varepsilon_{i,t}, \tag{1}$$

where $m_{t,s}(\cdot)$ are unknown, characteristic-specific functions. The group LASSO nonparametrically estimates the functions $m_{t,s}(\cdot)$ and sets them to zero if a characteristic (i.e., the "group") is deemed irrelevant for predicting returns. Hence, the procedure achieves model selection.

Interestingly, the functions $m_{t,s}(\cdot)$ can be interpreted similarly to portfolio sorts. To see this, we follow Freyberger et al. (2020) and partition the support into L intervals, whose endpoints (often referred to as "knots") are the percentiles of the rank-transformed characteristic. If we were to approximate the function associated with the latter as piece-wise constant in each of the L intervals, this would correspond exactly with standard portfolio sorts, with each of the intervals, possibly, having forecasting power for excess returns. However, to accommodate nonlinearity in the predictive relation, we take a different route and approximate the characteristic function $m_{t,s}(\cdot)$ by a quadratic spline on each interval, thereby making the function continuously differentiable on the unit interval. As a result, the conditional mean can be interpreted as capturing the predictive impact from smooth extensions of standard, characteristics-based, portfolio sorts, which is nested as a special case.

To explicate these points, we decompose each characteristic function, $m_{t,s}(\cdot)$, as a linear combination of $L + 2$ quadratic basis functions, that is,

$$m_{t,s}(c) \simeq \sum_{k=1}^{L+2} \beta_{t,s,k} \times p_k(c), \tag{2}$$

where $p_k(c)$ are known functions (quadratic) and $\beta_{t,s,k}$ are parameters to be estimated, capturing the predictive ability of a "smooth" characteristic sort. We will demonstrate below that allowing for such nonlinearity is important for characterizing the predictive power for "extreme" percentiles of the significant, rank-transformed, option characteristics. Evidently, the number of intervals L is a user-specified tuning parameter, analogous to the number of portfolios in standard sorts, and its selection involves a bias-variance trade-off. In particular, as L increases, the precision of the approximation (2) improves, but since the number of parameters increases – so does the variance.

The AG-LASSO involves two steps. First, let $\mathcal{S} \equiv \{(1, \ldots, S) \otimes (1, \ldots, L+2)\}$, then the coefficients in the approximation (2) are obtained as,

$$\boldsymbol{\beta}_t = \underset{b_{s,k}:(s,k)\in\mathcal{S}}{\operatorname{argmin}} \sum_{i=1}^{N} \left(R_{i,t} - \sum_{s=1}^{S} \sum_{k=1}^{L+2} b_{s,k} \times p_k(\tilde{C}_{s,i,t-1}) \right)^2 + \lambda_1 \sum_{s=1}^{S} \left(\sum_{k=1}^{L+2} b_{s,k}^2 \right)^{1/2}, \tag{3}$$

where $\boldsymbol{\beta}_t$ is an $S(L + 2) \times 1$ vector of (stacked) parameter estimates and λ_1 is a first-step penalization coefficient. Rather than penalizing the individual coefficients, the group LASSO penalizes all coefficients associated with a given characteristic (or group), ensuring that functions associated with irrelevant characteristics are set to zero. Importantly, the penalization component of the objective function facilitates settings with many characteristics and, following Yuan & Lin (2006), we choose λ_1 in a data-dependent way by minimizing the Bayesian information criterion.

The second step comprises the "adaptive" part of the procedure. Specifically, the LASSO (often) selects too many characteristics in the first step, including some irrelevant ones. To combat this issue, the second step applies *characteristic-specific* weights in the penalty component of the objective function (3) (see the online appendix in Freyberger et al. (2020), who also discuss model selection, consistency and efficiency of the estimates).[10] The weighting in the second step alleviates the model-section issues, ensuring that, asymptotically, we will select the correct characteristics.[11]

3.7.2 Empirical Characteristic Selection and Nonlinear Modeling

We use the AG-LASSO to examine whether a given option characteristic adds incremental information to the 62 firm characteristics from Freyberger et al. (2020) as well as the four $\mathbb{P}$-distribution control

[10] The model selection issue in the first step, motivating the two-step approach, is well-known from linear models; see, e.g., Meinshausen & Bühlmann (2006) and Zou (2006), who show that LASSO does not achieve consistent model selection unless restrictive conditions on the design matrix are satisfied.

[11] Note that adaptive shrinkage represents one solution to the first-step model selection issue. An alternative solution is to impose group sparsity, e.g., Nardi & Rinaldo (2008) and Lounici, Pontil, van der Geer & Tsybakov (2011), which can deliver better theoretical properties and, if used in conjunction with a post-LASSO approach as in Feng et al. (2020), can restore standard asymptotic properties. We do not pursue such alternatives here.

variables. Specifically, in Table 5, we list the selected variables when sequentially adding each option characteristic to the baseline set of control variables, allowing each to exhibit a nonlinear predictive relation. There are several interesting observations. First, only 7 out of 17 of the option characteristics are selected by the AG-LASSO. Apart from ΔPIV and β_{Vol}, these are the same characteristics that emerge significantly in Table 2 (where the former are "only" significant on a 5%, respectively, 10% significance level). Hence, there is a remarkable consistency between our analysis of portfolio sorts and this unconditional analysis utilizing *joint* selection among large sets of characteristics. Importantly, despite ΔPIV passing all of our comprehensive tests in Tables 2-4, the predictor succumbs to irrelevance once we select the characteristics unconditionally and accommodate nonlinearity.

Second, nonlinearity is important and prevalent among the significant option characteristics. To highlight this point and the importance of including controls, we visualize the nonparametric function associated with a significant ($\mathtt{IVS}_{\mathrm{ATM}}$) and an insignificant (VOV) predictor in Figure 3, with and without including the controls. In particular, for the univariate AG-LASSO estimates, we observe that both characteristics appear significantly, judging by the (point-wise, correct) 95% confidence intervals. However, all predictive power from VOV dissipates when including control variables, while the coefficient estimates for $\mathtt{IVS}_{\mathrm{ATM}}$ are largely unchanged. Moreover, consistent with the so-called "rank effect" (e.g., Hartzmark (2015)), the predictive information is mainly generated by small (low rank) and large (high rank) values of the option characteristic. The relation is clearly nonlinear, with the slope being particularly steep at large values of the characteristic. In analogy with standard portfolio sorts, this corresponds to the predictive power arising mainly from the extreme portfolios. Importantly, Figure 4 demonstrates that the rank effect is prevalent in all the IV spread variables.

This point is corroborated by Table B.2 in Appendix B, which shows the high-minus-low return spread as a function of the number of portfolios included in standard portfolio sorts for all option characteristics. While a few option characteristics exhibit larger returns for more granular long-short portfolios, the effect is particularly pronounced for the IV spread variables, underscoring their significance as cross-sectional return predictors as well as the propensity of the predictive information to manifest itself in extreme percentiles and generate nonlinearity in the predictive relation.

Third, there is an equally impressive consistency among the selected firm characteristics. Specifically, for the significant option characteristics, they are often complemented by Beta, ΔShrout, Investment, LDP, PM adj, NOA and Total vol (again, see Freyberger et al. (2020)), suggesting that options provide valuable information, which is unspanned by a large set of firm characteristics. Indeed, the model selection results illustrate that option characteristics may be combined with a small set of firm characteristics to describe the cross-section of stock returns.

In sum, the empirical results from our portfolio sorting analysis and the AG-LASSO regressions point to the importance of including a large set of control variables and factor models when assessing the predictive power of option characteristics. The consistency between the results in Tables 2-5 further underscores our conclusions; namely, only $\mathtt{IVS}_{\mathrm{ATM}}$, $\mathtt{IVS}_{\mathrm{OTM}}$ SKEW and AVAR provide information in excess of firm characteristics and existing factor models. Specifically, while the many factor models in

Table 3 span the information in all but five option characteristics, the AG-LASSO analysis eliminates ΔPIV from further contention. Finally, but importantly, Figure 4 and Table B.2 illustrates that the predictive information in the significant option characteristics manifests itself nonlinearly in expected returns. In particular, they are all subject to the rank effect, where the predictability arises from extreme values of the characteristics. The patterns are remarkably similar.

4 Is Predictability Compensation for Structural Factor Risk?

The empirical results reveal strong cross-sectional predictability from four option characteristics associated with the IV spread; namely, $\texttt{IVS}_{\text{ATM}}$, $\texttt{IVS}_{\text{OTM}}$, SKEW and AVAR, whose portfolio sorts demonstrate significant and substantial risk premia across all combinations of control variables and factor models. Moreover, these are selected using the AG-LASSO. Most other characteristics appear significant for certain sets of controls, but lose significance in the most challenging tests or when selecting characteristics unconditionally while accommodating nonlinearity in the predictive relation. This section introduces additional controls inspired by the index option pricing literature and assesses whether predictability can be interpreted as compensation for exposure to structural factor risk.

Specifically, parametric option pricing models assert that the dynamics of the IV surface are driven by a combination of Gaussian and non-Gaussian shocks (i.e., jumps); the shocks to asset returns may be correlated with shocks to their volatility, that is, may be exposed to leverage effects; and that a time-varying low-dimensional factor structure not only generates IV smirks, but is also significantly priced, especially when studying index options (e.g., Andersen et al. (2015)). These models advocate a risk-based interpretation of the predictability results, that is, the structural risk factors comprising the option pricing model are significantly priced in the cross-section, and that option prices constitute an important source of information in identifying them. In contrast, there is a substantial literature (see the introduction and Section 2) arguing that options contain incremental information about returns due to the presence of informed traders or structural frictions such as short-selling constraints on assets with certain firm characteristics. However, before exploring frictions, mispricing or informed trading as possible channels for the predictability results, we need to include adequate controls to rule out a low-dimensional structural risk factor explanation. We first employ option surface expansions to deduce what risk factors may drive the variation in the predictors, before providing nonparametric ways to estimate them. Once we have motivated a new set of structural risk factor controls, we re-examine the information in the successful option characteristics.

4.1 Theoretical Foundation and IV Surface Expansions

To formalize the discussion and create hypotheses for the empirical analysis, we suppose that the asset price X_t is defined on a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$ and obey a general dynamic specification,

$$\frac{dX_t}{X_t} = \alpha_t dt + \sigma_t dW_t + \int_{\mathbb{R}} (e^x - 1)\tilde{\mu}(dt, dx), \tag{4}$$

where α_t and σ_t are the drift and volatility process, respectively, which are required to have càdlàg paths, W_t is a standard Brownian motion, and the martingale jump measure under the physical distribution $\mathbb{P}$, $\tilde{\mu}(dt, dx) = \mu(dt, dx) - \nu_t(dx)dt$, decomposes into a counting measure, $\mu(dt, dx)$, and a compensator describing the "average" number of jumps, $\nu_t(dx) \otimes dt$. Furthermore, we assume the existence of an alternative risk-neutral measure, $\mathbb{Q}$, under which X_t follows the dynamics,

$$\frac{dX_t}{X_t} = (r_t - \delta_t)dt + \sigma_t dW_t^{\mathbb{Q}} + \int_{\mathbb{R}} (e^x - 1)\tilde{\mu}^{\mathbb{Q}}(dt, dx), \tag{5}$$

where r_t and δ_t denote the instantaneous risk-free rate and dividend yield of X_t, respectively, $W_t^{\mathbb{Q}}$ is similarly a $\mathbb{Q}$-Brownian motion, and the corresponding $\mathbb{Q}$ martingale measure is given by $\tilde{\mu}(dt, dx) = \mu(dt, dx) - \nu_t^{\mathbb{Q}}(dx)dt$, where $\nu_t^{\mathbb{Q}}(dx) \otimes dt$ is the compensator under $\mathbb{Q}$.[12]

In this general setting, we may use options with different maturities and strike prices to learn about the components of the underlying asset price, X_t, via their risk neutral expectations. That is, we can recover knowledge about the underlying structural risk factors, without necessarily assuming a parametric model for the option surface and without knowledge of whether these factors aid in predicting the returns on the underlying asset out of sample. To see this, we first follow Bollerslev & Todorov (2014) by letting $O_{t,\tau}(k)$ denote the time t price of an OTM option with expiration τ and log-moneyness $k = \log(K/F_{t,\tau})$, where $F_{t,\tau}$ is the futures price of X_t. Then, under general conditions on the price process in equations (4)-(5), Carr & Wu (2003) and Bollerslev & Todorov (2014) show that

$$\frac{e^{r_{t,\tau}} O_{t,\tau}(k)}{F_{t,\tau}} \simeq \begin{cases} \int_t^{t+\tau} \int_{\mathbb{R}} (e^x - e^k)^+ \mathbb{E}_t^{\mathbb{Q}}(\nu_s^{\mathbb{Q}}(dx))ds, & \text{if } k > 0, \\ \int_t^{t+\tau} \int_{\mathbb{R}} (e^k - e^x)^+ \mathbb{E}_t^{\mathbb{Q}}(\nu_s^{\mathbb{Q}}(dx))ds, & \text{if } k < 0, \end{cases} \tag{6}$$

where $r_{t,\tau}$ is the risk-free interest rate over the time interval from t to $t + \tau$. Formally, this expansion result holds for short-dated and far-OTM options, that is, as $\tau \to 0^+$ and when the log-moneyness diverges, $k \to \pm\infty$, for calls and puts, respectively. Importantly, the expansion suggests that the variation in the $\texttt{IVS}_{\text{OTM}}$, `SKEW` and `AVAR` measures may be driven by variation in the jump compensator, at least partially, since the variables are constructed using 30-day OTM options.

Next, to elaborate on the expansion in (6) and to examine $\texttt{IVS}_{\text{ATM}}$, in particular, which is constructed using near-ATM 0.50-delta options, it is instructive to impose stronger assumptions on the risk-neutral price dynamics in equation (5).[13] Specifically, we follow Medvedev & Scaillet (2007) and assume a jump-diffusion model with stochastic volatility, whose components are given by,

$$d\sigma_t = \tilde{\alpha}(\sigma_t) + \tilde{\sigma}(\sigma_t)\Big[\rho dW_t^{\mathbb{Q}} + \sqrt{1-\rho^2} dB_t^{\mathbb{Q}}\Big], \quad \int_{\mathbb{R}} (e^x - 1)\tilde{\mu}^{\mathbb{Q}}(dt, dx) = dJ_t^{\mathbb{Q}} - \nu_t^{\mathbb{Q}}(\sigma_t)dt, \tag{7}$$

[12]The existence of the risk-neutral measure follows from no-arbitrage and mild technical conditions; see, e.g., Duffie (2001).

[13]We emphasize, however, that the results hold more generally. In particular, Figueroa-Lopez, Gong & Houdre (2016), Figueroa-Lopez & Olafsson (2016), Ait-Sahalia, Li & Li (2020*a*, 2020*b*) show that equivalent short-term, near-ATM expansions of the IV surface hold under very mild conditions on the stochastic volatility, jump and leverage processes. However, for ease of exposition, we refrain from stating them in full generality.

where $\tilde{\alpha}(\sigma_t)$ and $\tilde{\sigma}(\sigma_t)$ are the drift and volatility-of-volatility, $B_t^{\mathbb{Q}}$ is a standard Brownian motion, ρ captures the leverage effect, and $J_t^{\mathbb{Q}}$ is an independent Poisson process, which has constant expected jump size, $\mathbb{E}^{\mathbb{Q}}(\Delta J)$, and a jump intensity, $\lambda^{\mathbb{Q}}(\sigma_t)$, that may depend on σ_t in a deterministic way, such that the jump compensator, $\nu_t^{\mathbb{Q}}(\sigma_t) = \lambda^{\mathbb{Q}}(\sigma_t)\mathbb{E}^{\mathbb{Q}}(\Delta J)$, may similarly depend on σ_t. Moreover, we define the "volatility standardized" log-moneyness as $\theta_t = k/(\sigma_t\sqrt{\tau})$ and let $\texttt{IV}(\theta_t, \tau, \sigma_t)$ denote the Black-Scholes IV associated with the OTM option $O_{t,\tau}(k)$. Then, Medvedev & Scaillet (2007) derive an expansion of $\texttt{IV}(\theta_t, \tau, \sigma_t)$ as the tenor $\tau \to 0^+$, when the log-moneyness k is fixed,

$$\texttt{IV}(\theta_t, \tau, \sigma_t) = \sigma_t + \mathcal{I}_t(\theta_t, \sigma_t)\sqrt{\tau} + O(\tau(1+\sqrt{\tau})), \quad \text{where} \tag{8}$$

$$\mathcal{I}_t(\theta_t, \sigma_t) = \frac{\rho\tilde{\sigma}(\sigma_t)}{2\sigma_t\sqrt{\tau}}k - \nu_t^{\mathbb{Q}}(\sigma_t)\frac{\mathcal{N}(\theta_t)}{\mathcal{N}'(-\theta_t)} + \eta_t^{\mathbb{Q}}(\sigma_t)\frac{1}{\mathcal{N}'(-\theta_t)}, \quad \eta_t^{\mathbb{Q}}(\sigma_t) = \lambda^{\mathbb{Q}}(\sigma_t)\mathbb{E}^{\mathbb{Q}}(\Delta J_t)^+, \tag{9}$$

with $\mathcal{N}'(\cdot)$ and $\mathcal{N}(\cdot)$ being the pdf and cdf of the standard Gaussian distribution, respectively. In contrast to the deep OTM approximation in (6), the alternative expansion result in (8) suggests that the IV smile for short-dated options and moderate levels of log-moneyness (i.e., when k is fixed) is first-order driven by the term $\mathcal{I}_t(\theta_t, \sigma_t)$, which contains information about four structural components of the option pricing model; the jump compensator ($\nu_t^{\mathbb{Q}}(\sigma_t)$ and $\eta_t^{\mathbb{Q}}(\sigma_t)$), the leverage effect ($\rho$), the spot volatility ($\sigma_t$) and the volatility-of-volatility ($\tilde{\sigma}(\sigma_t)$). Moreover, the expansion speaks directly to the shape of the IV smirk for near-ATM options (i.e., k close to 0) as $\tau \to 0^+$,

$$\frac{\partial \texttt{IV}(\theta_t, \tau, \sigma_t)}{\partial k}\Big|_{k=0} \to \frac{\rho\tilde{\sigma}(\sigma_t)}{2\sigma_t} + \frac{\nu_t^{\mathbb{Q}}(\sigma_t)}{\sigma_t}, \tag{10}$$

where these dependencies become evident. This suggests that the variation of $\texttt{IVS}_{\text{ATM}}$, $\texttt{IVS}_{\text{OTM}}$, $\texttt{SKEW}$ and $\texttt{AVAR}$ could be driven by four risk factors; jumps, leverage, volatility and volatility-of-volatility. When these insights are combined with the expansion in (6), we naturally expect the variables $\texttt{IVS}_{\text{OTM}}$, $\texttt{SKEW}$ and $\texttt{AVAR}$ to be more dependent on jumps than $\texttt{IVS}_{\text{ATM}}$.

It is important to realize that these surface expansions only suggest that the variation in the successful option characteristics is driven by structural risk factors. They do not speak to whether such factors are priced in the cross-section. Nevertheless, these risk factors are natural control variables when attempting to further decompose the information embedded in the predictors.

4.2 Option-based Control Variables

The option surface expansions provide rigorous motivation for examining whether the cross-sectional predictive ability of IV spread characteristics $\texttt{IVS}_{\text{ATM}}$, $\texttt{IVS}_{\text{OTM}}$, $\texttt{SKEW}$ and $\texttt{AVAR}$ can be interpreted as compensation for option-implied jump risk, leverage effects, volatility and volatility-of-volatility. To this end, we construct the following option-based control variables:

- **Jump variables**. We include nonparametric estimates of the, possibly, time-varying level and shape parameters for positive and negative jumps, thus allowing for asymmetry.[14] These are denoted by $\phi_t^{\pm}$ and $a_t^{\pm}$, respectively. Moreover, we estimate the left and right jump intensity, denoted by $\texttt{LJI}_t$ and $\texttt{RJI}_t$. We rely on the procedures by Bollerslev & Todorov (2014) and Bollerslev, Todorov & Xu (2015), which are described in Appendix A.[15]

- **Volatility estimate**. We approximate the spot volatility using one-month implied volatility, averaged over 0.50 delta call and -0.50 delta put options. It follows from Durrleman (2008) that short-horizon near-ATM converges to the spot volatility; see also equation (8) as $\tau \to 0^+$.

- **Volatility-of-volatility**. We use the estimator from Section 3.2.

- **Leverage**. We propose to estimate the leverage using the expansion from (10). Specifically, using options with a one-month maturity, we estimate

$$\texttt{leverage} = \left(\frac{\texttt{IV}(c, 0.45) + \texttt{IV}(p, -0.45)}{2}\right) \times \left(\frac{\texttt{IV}(c, 0.45) - \texttt{IV}(p, -0.45)}{k(c, 0.45) - k(p, -0.45)}\right),$$

where $\texttt{IV}(c, 0.45)$ and $k(c, 0.45)$ denote the IV and log-moneyness, respectively, for a call option with delta equal to 0.45, and $\texttt{IV}(p, -0.45)$ and $k(p, -0.45)$ are corresponding put observations. This isolates information about leverage, vol-of-vol and jumps.[16]

Our dataset of option characteristics is therefore expanded with a set of option-based control variables consisting of `LJI`, `RJI`, `vol`, `vol-of-vol` and `leverage`. These span structural risk factors that are typically stipulated to drive the dynamics of the IV surface by the index option pricing literature. Whereas long-short portfolio results based on `vol` and `vol-of-vol` are given in Table 1, both yielding a negative risk premium, we provide corresponding portfolio sorts results for `LJI`, `RJI` and `leverage` in Table B.1. In particular, these reveal a negative risk premium associated with `LJI` and positive risk premia with `RJI` and `leverage`. Hence, stocks with a high `LJI` *underperform* relative to stocks with a low `LJI`. Conversely, stocks with a high `RJI` *outperform* stocks with a low `RJI`. The signs suggest that option prices convey information about shifts in the risk-neutral distribution and these predict corresponding future shifts in the physical distribution of returns. However, the signs of the risk premia are *not* consistent with compensation for exposure to elevated jump risk. For `leverage`, note that

$$\texttt{leverage} \simeq \frac{\rho\tilde{\sigma}(\sigma_t)}{2} + \lambda^{\mathbb{Q}}(\sigma_t)\mathbb{E}^{\mathbb{Q}}(\Delta J), \tag{11}$$

as $\tau \to 0^+$ and $k \to 0$, using the expansion in (10). Hence, the leverage effect may arise through continuous (ρ) as well as discontinuous ($\mathbb{E}^{\mathbb{Q}}(\Delta J)$) channels and is typically negative for stocks that

[14] Note that these estimates are nonparametric in the sense that they apply for a general class of jump processes. Of course, the model still requires the absence of arbitrage as well as other mild, mostly technical, assumptions to remain valid.

[15] Our main analysis is carried out using the aggregate measures $\texttt{LJI}_t$ and $\texttt{RJI}_t$, rather than $\phi_t^{\pm}$ and $a_t^{\pm}$ for simplicity of exposition. However, qualitatively similar results are obtained when including $\phi_t^{\pm}$ and $a_t^{\pm}$.

[16] As a robustness check, we have constructed other, more conventional, leverage effect estimates using the correlation between the daily returns and daily *innovations* in our volatility estimate over a look-back period of 250 days. The results are similar to those reported for our expansion-based variable and, thus, left out for brevity.

exhibit a "standard" IV smirk. Moreover, we can isolate these effects by including `LJI`, `RJI` and `vol-of-vol` in subsequent the spanning regressions. Empirically, we observe from Table B.1 that stocks having a large negative leverage effect, and thus a steep IV smirk, perform worse than stocks with a corresponding smaller component. Again, this is consistent with correct predictions of shifts in the distribution of the underlying asset returns, *not* with compensation for systematic risk.

The IV expansions and option-based control variables allow us to formulate empirical hypotheses. In particular, if the variation of the significant IV spread-relative option characteristics is explained by the four risk factors, we expect stocks with standard IV smirks to load positively on `LJI` and `vol-of-vol` as well as negatively on `leverage` and `vol`. However, again, such loadings are not necessarily consistent with compensation for risk, as seen in Table B.1.

4.3 Controlling for $\mathbb{Q}$ Factors

Motivated by the option surface expansions, we proceed evaluating the cross-sectional information embedded in the IV spread variables. Specifically, we examine the significant option characteristics from three different perspectives: (i) We compute the option-based control characteristics for the successful option characteristic portfolios; (ii) We test whether long-short portfolios constructed using the option-based controls span the corresponding returns for the option characteristics; (iii) We add the option-based controls to the variable set in the AG-LASSO framework.

First, in Table 6, we provide option-based control characteristics for the ten portfolios associated with a sort on each of the IV spread variables. The excess return results verify the performance of the long-short portfolios in Table 1; the returns are monotonically decreasing from portfolios one through ten. In addition, we observe a positive monotonic relation to `LJI`, consistent with an IV smirk across the volatility surface. The results are less clear for the remaining option-based controls. Specifically, we find no noticeable dependencies on `RJI`, which, as a result, is dropped from the portfolio spanning analysis. Similarly, `vol-of-vol` exhibits a slight U-shaped pattern. For `leverage`, the dependence seems to be negative, however, measured with noise at the "1" and "10" portfolios. Lastly, the corresponding results for the `vol` control variable are mixed across the option characteristics.

The impact and interpretation of the option-based controls, however, should not be viewed in isolation. Hence, in Table 7, we provide spanning regressions for the IV spread variables using the option controls and sequentially add the five $\mathbb{P}$-distribution controls and the five RP-PCs from the 62 firm characteristics. This will help us to determine whether the information in the successful option characteristics are spanned by structural factor risk under $\mathbb{Q}$, related measures under $\mathbb{P}$ as well as a large number of firm characteristics. This analysis reveals several interesting results. First, from Panel A, which only includes the option-based controls as regressors, we find `leverage` is significant for all IV spread characteristics, and `LJI` and `vol` to be significant for those based on OTM options, consistent with the predictions from the expansions in (6) and (10). Second, when comparing against Table 2, we observe that the $\mathbb{Q}$-controls explain the variation much better than the FF6 model. For example, for $\texttt{IVS}_{\text{ATM}}$, the alpha drops from -1.80 to -1.13, albeit remaining significant, and the R^2 has increased from 8% to 34%. Third, when adding both $\mathbb{P}$-controls and the RP-PCs in Panels B and C, the performance of the spanning models further improves. In fact, we find that this alternative factor model has eliminated the alpha associated with $\texttt{IVS}_{\text{OTM}}$ and `SKEW` characteristics as well as reduced the alpha from -1.13 to -0.82 for $\texttt{IVS}_{\text{ATM}}$ and from -0.56 to -0.37 for `AVAR` when compared against the corresponding RP-PC5 results in Table 3. The alpha reductions and improvements in the R^2 are even greater if benchmarking against the FF6 model with $\mathbb{P}$-controls in Table 4.

Fourth, `leverage`, `LJI` and `vol` remain strong explanatory variables despite adding $\mathbb{P}$-distribution controls and RP-PCs based on firm characteristics. Moreover, the respective coefficient signs are consistent with an IV smirk. However, given that the risk premium estimates for the option-based controls in Tables 1 and B.1 are inconsistent with a risk-return trade-off, the regression loadings suggest that the predictive channels for the option characteristics are more likely made up of important incremental information about stock mispricing and future realized return distributions. The most important of the $\mathbb{P}$-controls for $\texttt{IVS}_{\text{OTM}}$ and `SKEW` is the max statistic. Similarly, tail and low-frequency risk are significant for `AVAR`. This suggests that the option characteristics also contain information about relative over- and undervaluation of stocks and their exposure to tail as well as disaster risk.

In sum, our results demonstrate that we can give a structural interpretation to (part of) the variation of the IV spreads; particularly, in terms of `leverage`, `LJI` and `vol`, which contain significant explanatory power despite including many firm characteristics and $\mathbb{P}$-distribution controls in the spanning regressions. However, the sign and magnitude of the predictive implications for the option characteristics as well as their structural components, including both the regression loadings and residual alpha for $\texttt{IVS}_{\text{ATM}}$ and `AVAR`, fail to facilitate a clear risk-reward interpretation. Rather, our results show that the IV spread characteristics contain important incremental information about asset (over-)valuation, mispricing and future return realizations, consistent with informed trading in option markets. Indeed, Table B.3 in Appendix B corroborates these findings by showing that the IV spreads remain significant predictors of raw stock returns despite including the option-based controls among the candidate predictor set in the unconditional AG-LASSO analysis. This information as well as the predictive channels are further decomposed in the next section.

5 Mispricing, Valuation and Limits to Arbitrage

Section 3 reveals the existence of four option characteristics with strong predictive power for returns on the underlying assets, and Section 4 demonstrates that two of these predictors retain significant alpha when controlling for firm characteristics as well as variables that speak to distribution features under both the $\mathbb{P}$ and $\mathbb{Q}$ measures. Moreover, the spanning regressions suggest that the incremental information is linked to asset mispricing, (over-)valuation and excess information about future tail return realizations. This section explores these channels in greater detail, providing additional perspectives on the predictive information as well as robustness checks.

5.1 Performance of the Long and Short Legs

Figure 4 illustrates that low and high values of the successful option characteristics forecast future high and low returns, respectively. This effect is pronounced for the extreme "1" and "10" portfolios and remarkably similar across predictors. This is also evident from Table 1 where the "1" portfolios achieve annualized returns between 16.11% and 18.34% and "10" portfolios typically deliver close to zero, or even negative, returns. Moreover, as documented by our extensive spanning and model selection analyses in Sections 3 and 4, this asymmetric relationship cannot be attributed to factor exposures and firm characteristics alone. In fact, as visualized by the historical performance for the long-short portfolios of $\texttt{IVS}_{\text{ATM}}$ and `AVAR` in Figure 5, the excess returns are strikingly pervasive.

Asymmetric relations of this kind are well-documented in the asset pricing literature and naturally calls for a cautious interpretation. For example, Chen, Da & Huang (2019) find that limits to arbitrage hinder informed traders' abilities to correct mispricing, suggesting that some of the hypothesized excess information in the option characteristics may be due to trading frictions. Hence, we further examine the predictive information of the option characteristics via interactions with measures of mispricing and limits to arbitrage as well as restrict the sample to the more liquid S&P 500 universe.

5.2 Misspricing and Valuation

We provide a deeper dive into the interaction between option characteristics and information about asset (over-)valuation in Table 8 using conditional double sorts with the mispricing scores from Stambaugh et al. (2015) and Stambaugh & Yuan (2017).[17] As the SYY data is only available until 2016, we limit our analysis to the time period from 1996 through 2016. Specifically, we initially divide the stocks into a three groups according to the SYY mispricing score before carrying out a portfolio sorting exercise based on the successful option characteristics within each of the groups. A high SYY score indicates over-valuation and, thus, signals low future stock returns. Table 8 documents an interesting interaction. The negative predictability from a high value of the four option characteristics is more pronounced for stocks with high SYY score, i.e., for stocks that are classified as overvalued. For example, the returns to stocks in portfolio 10 (high value of the option characteristic) ranges between 0.6-5% annually if the sort is unconditional relative to the SYY score. Specifically, conditioning on stocks with a high SYY score, we observe negative returns around -5% for portfolio 10. A similar pattern is seen for portfolio 1 (low value of the option characteristics), albeit substantially less pronounced. Hence, the two measures display positive correlation, consistent with the significant loading on the max statistic in Table 7. However, the correlation between the SYY score and the option characteristics is low, ranging between 0.025 for $\texttt{IVS}_{\text{ATM}}$ and 0.054 for `AVAR`; alternatively, the correlation in ranks is between 0.027 for $\texttt{IVS}_{\text{ATM}}$ and 0.13 for `AVAR`. Clearly, the option characteristics are not solely capturing the (over-)valuation information embedded in the SYY score.

[17]The mispricing scores are obtained from Robert Stambaugh's website. We thank him for making them available.

5.3 Limits to Arbitrage

The strong asymmetric excess return pattern across decile portfolios, the pervasiveness of the outperformance of the long-short portfolio, the significant loading on the max statistic in Table 7, and the positive correlation with SYY mispricing score in Section 5.2, all raise the question if the cross-sectional predictability from the successful option characteristics is limited to (possibly, overvalued) stocks that are very costly to sell short. Absent from actual rebate rates, this question is virtually impossible to answer exhaustively. However, to examine a potential explanation based on possible limits to arbitrage in greater detail, we employ two proxies for trading frictions.

First, similarly to the (over-)valuation analysis in Section 5.2, we carry out a conditional double sort using the Corwin & Schultz (2012) liquidity measure. The latter indicates trading frictions, with a low liquidity value implying that the stocks are difficult to trade. Hence, the results, presented in Table 9, speak to whether the strong long-short portfolio performance can actually be realized by an investor. Interestingly, we find that the returns to stocks in portfolio 1 are strikingly similar across the three liquidity groups. In contrast, there is clearly a premium associated with (low) liquidity for stocks belonging to portfolio 10. Consequently, the return spread is larger for the long-short portfolios in the low liquidity bin. Importantly, however, liquidity provides only a partial explanation, as return spread remains substantial for high liquidity stocks.

Second, we carry out a similar conditional double sort using idiosyncratic volatility (relative to the Fama & French (1993) three-factor model), as an alternative proxy for trading frictions. This is advocated by, e.g., Wurgler & Zhuravskaya (2002) and Stilger et al. (2017). The results of this conditional double sort, reported in Table 10, mirror the corresponding ones obtained for the SYY mispricing score in Section 5.2, both qualitatively and quantitatively. Specifically, we find that stocks belonging to portfolio 10 conditional on having high idiosyncratic volatility underperform the corresponding portfolio in the unconditional sorts by 10% per annum. Moreover, there is substantially less return dispersion for portfolio 1. Consequently, part of the excess performance obtained for the successful option characteristics may not be realizable by investors due to trading frictions.

In sum, both our proxies for trading frictions provide partial explanations for the return spread to the option characteristics. That is, the spread is larger for groups that are deemed more difficult to trade. However, as "10-1" return spreads remain substantial for groups that have high liquidity or low idiosyncratic volatility, this suggests that limits to arbitrage only provide a partial explanation of the premium, similarly to asset overvaluation and mispricing in Section 5.2.[18]

5.4 Predicting the S&P 500 Universe

The conditional double sorts using liquidity and idiosyncratic volatility as proxies for trading frictions demonstrates that part of the performance gains for portfolios sorted on the successful option characteristics cannot be realized by investors due to limits to arbitrage. While it is impossible to

[18] We carried out a similar analysis using size as a proxy for trading frictions, since it is more difficult to trade small stocks. The results, presented in Table B.4 of Appendix B, are similar to those in Tables 9 and 10.

comprehensively address these concerns for all stocks and the full time period, we can provide partial answers by restricting attention to very large firms; namely, those belonging to the S&P 500 index at the time of portfolio formation.[19] Similarly to all of our previous analyses, we sort stocks into portfolios based on their option characteristics and study the performance of the resulting portfolios. However, due to a smaller number of securities in the universe, we sort stocks into five rather than ten bins, such that the resulting portfolios remain well-diversified. Table 11 reports the performance of the long-short portfolios for all the option characteristics in Section 3.2. Importantly, by contrasting the results in Table 11 with Table 1, it is apparent that the predictability is generally much weaker for the S&P 500 stocks. It is, however, noteworthy, that the strongest performance in terms of Sharpe ratios is still delivered by sorting stocks according to $\texttt{IVS}_{\text{ATM}}$, $\texttt{IVS}_{\text{OTM}}$ and `SKEW`. This demonstrates that the predictability achieved by these option characteristics is not confined to small stocks, but is also prevalent among the largest stocks in the US economy.

Importantly, given that we are dealing with very large stocks in this analysis, it is natural to suspect that they may also be more exposed to market and factor risk. Hence, we need to examine if the strong performance of the long-short portfolios from Table 11 is, indeed, abnormal, that is, if significant alpha is attainable. We therefore repeat the previous analysis from Section 4 and confront the long-short portfolios for the successful option characteristics with the highest previous bar; namely, the five risk-premium principal components, the $\mathbb{P}$-distribution controls as well as the structural option-based control variables suggested by the theoretical IV expansions. The spanning regressions are provided in Table 12. Interestingly, they show that the option portfolios no longer deliver significant alpha at a 5% level. Moreover, the most significant regressors remain the `leverage` and `LJI` variables, with `vol-of-vol` and low-frequency market risk providing additional explanatory power. This shows that the predictive information for the S&P 500 can be characterized in terms of information about stock (over-)valuation and information about future tail return realizations. Hence, together with Tables 9 and 10, the results suggest that the reason for their success in the full cross-section can be explained by those two channels as well as limits to arbitrage.

6 Conclusion

We provide a comprehensive analysis of the predictive information in option characteristics for the cross-section of equity returns. While most do not hold up under scrutiny, few do indeed provide incremental information even after controlling for a large set of firm characteristics, known return predictors and, possibly, nonlinearities in the predictive relation. The successful ones are all related to the shape of the implied volatility smirk. Moreover, we carry out a structural analysis to further

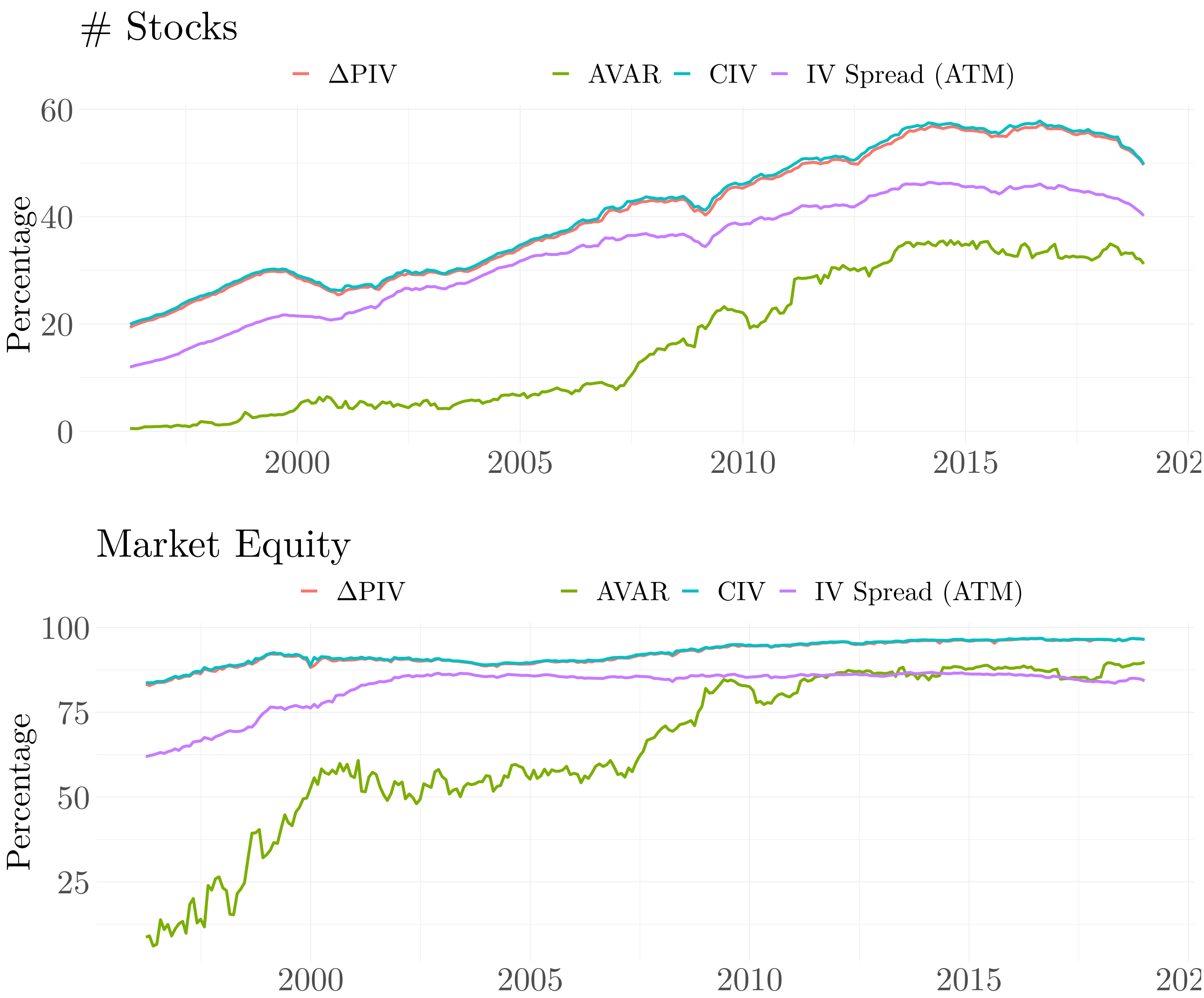
[19] A comprehensive examination would require knowledge of actual rebate rates and other implementation costs. Even if such data is available, merely "subtracting off" the trading cost yields an incomplete picture. If implementation costs are known ex-ante, it is safe to assume that a sophisticated financial agent would endogenize this information in her decision making and portfolio selection process – put simply, she would be trading off expected gains from buying or selling some security with the cost to do so.

understand the economic source(s) of the predictability. We find that the successful option characteristics provide information about asset mispricing, overvaluation and future tail return realizations. However, the mispriced assets may be subject to trading frictions and, thus, not easily be exploitable by investors. Nonetheless, the predictors embed important valuation and tail information.

Our paper provides the first comprehensive analysis of whether individual equity options contain significant and non-redundant information for the pricing of the cross-section of stock returns, while controlling for an extensive set of firm characteristics. Importantly, we demonstrate that options contain valuable information unspanned by firm characteristics. Since existing factor models such as the Fama & French (2015) five-factor model with momentum or the Hou et al. (2015) investment model ignore the relation between option measures and future returns, our analysis, thus, sheds light on why they fail to adequately explain the cross-section of stock returns.[20] In fact, our results suggest that a promising avenue to build the next generation of factor models will be to leverage the information in options. We leave this exciting and important research topic for future research.

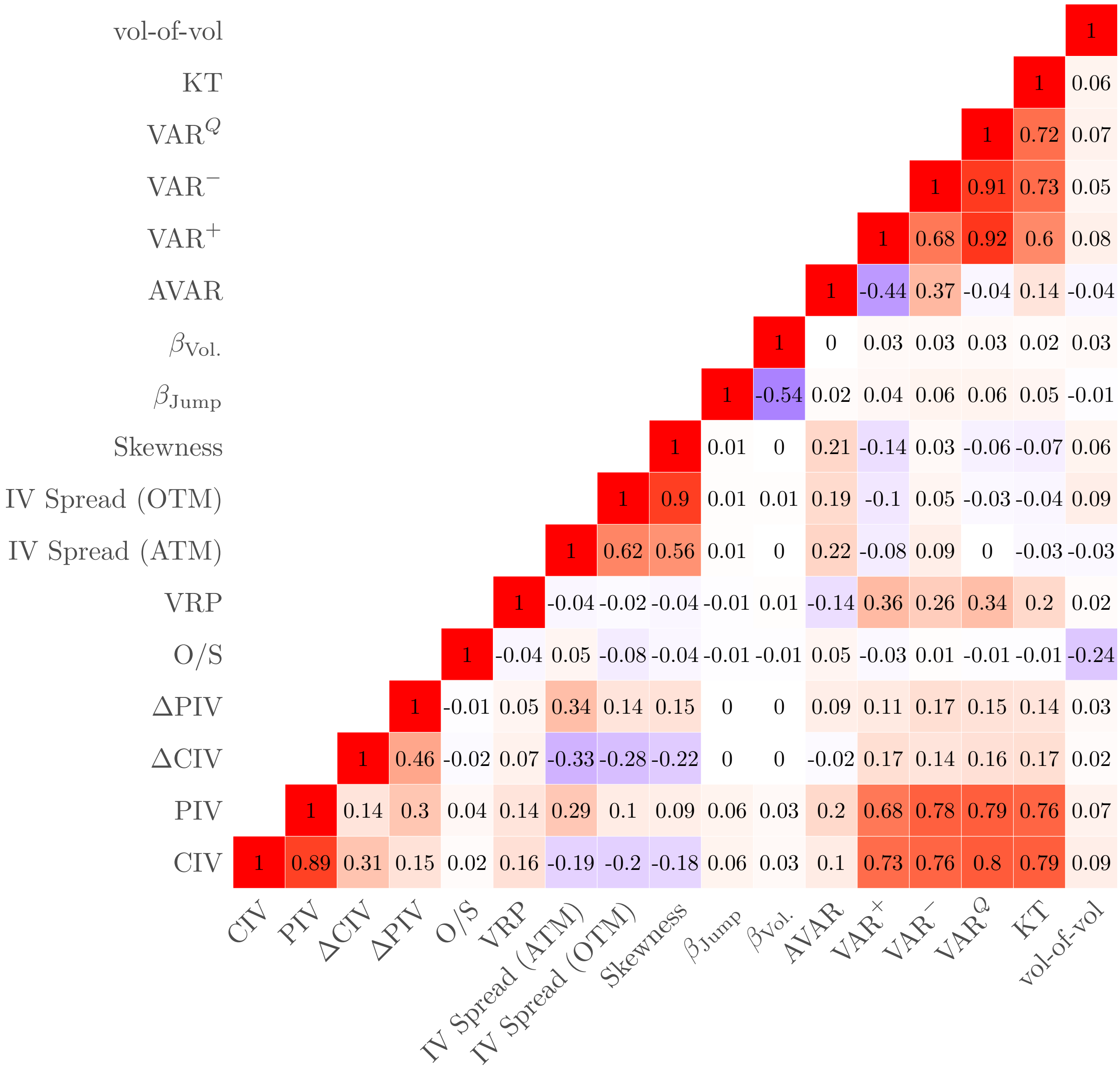
[20]For example, He, Huang, Yuan & Zhou (2021) show that the pricing errors of these factor models are not only large, they even earn profitable abnormal returns.

Figure 1: **Option Coverage**



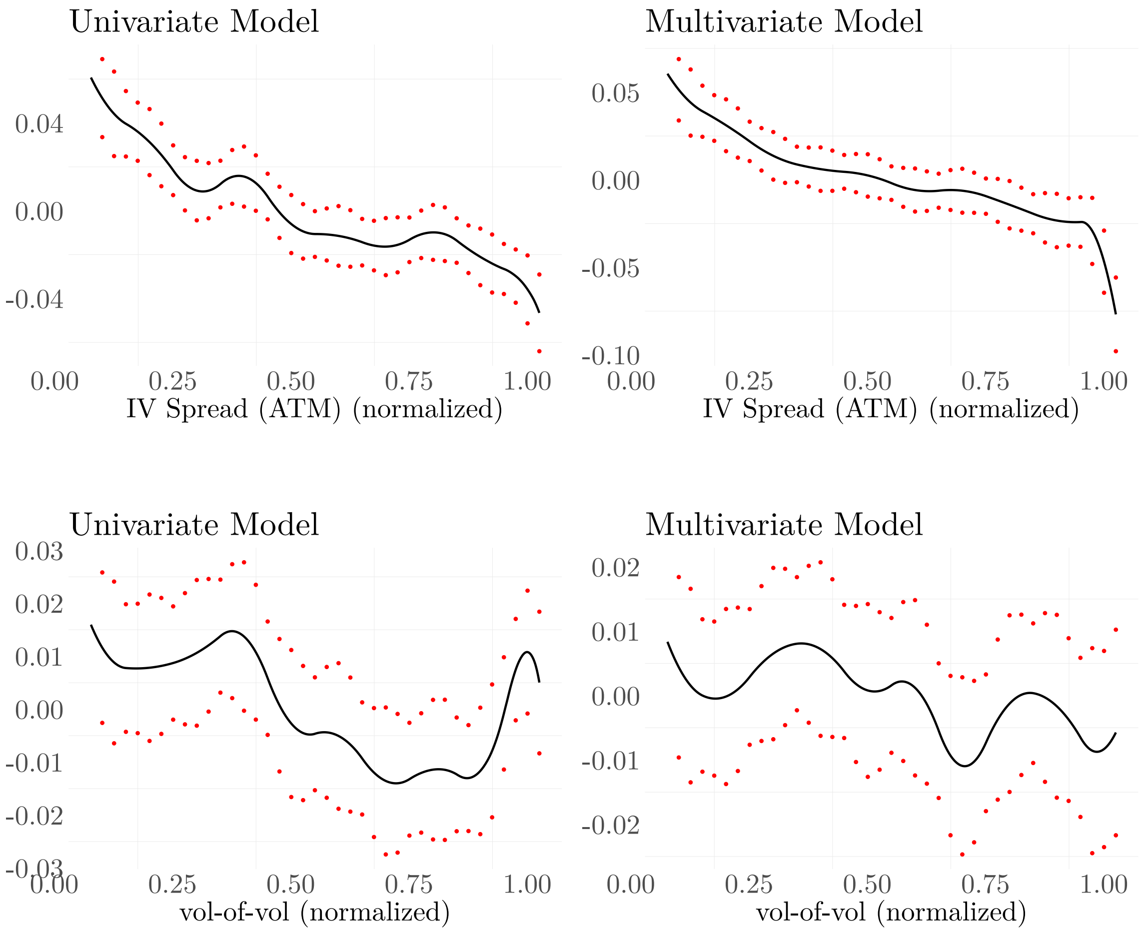
The upper panel of the figure shows the percentage of stocks (relative to all NYSE, AMEX and NASDAQ stocks in CRSP) for which we can compute various predictors. The lower panel illustrates what fraction of total market capitalization (NYSE, AMEX, NASDAQ) we can compute the predictors. ΔPIV are monthly innovations in at-the-money put-implied volatility, AVAR is variance asymmetry, CIV is at-the-money call implied volatility and IV Spread (ATM) is the difference between at-the-money put an call implied volatility. The predictors are described in detail in Section 3.2.

Figure 2: **Correlation between Option Characteristics**



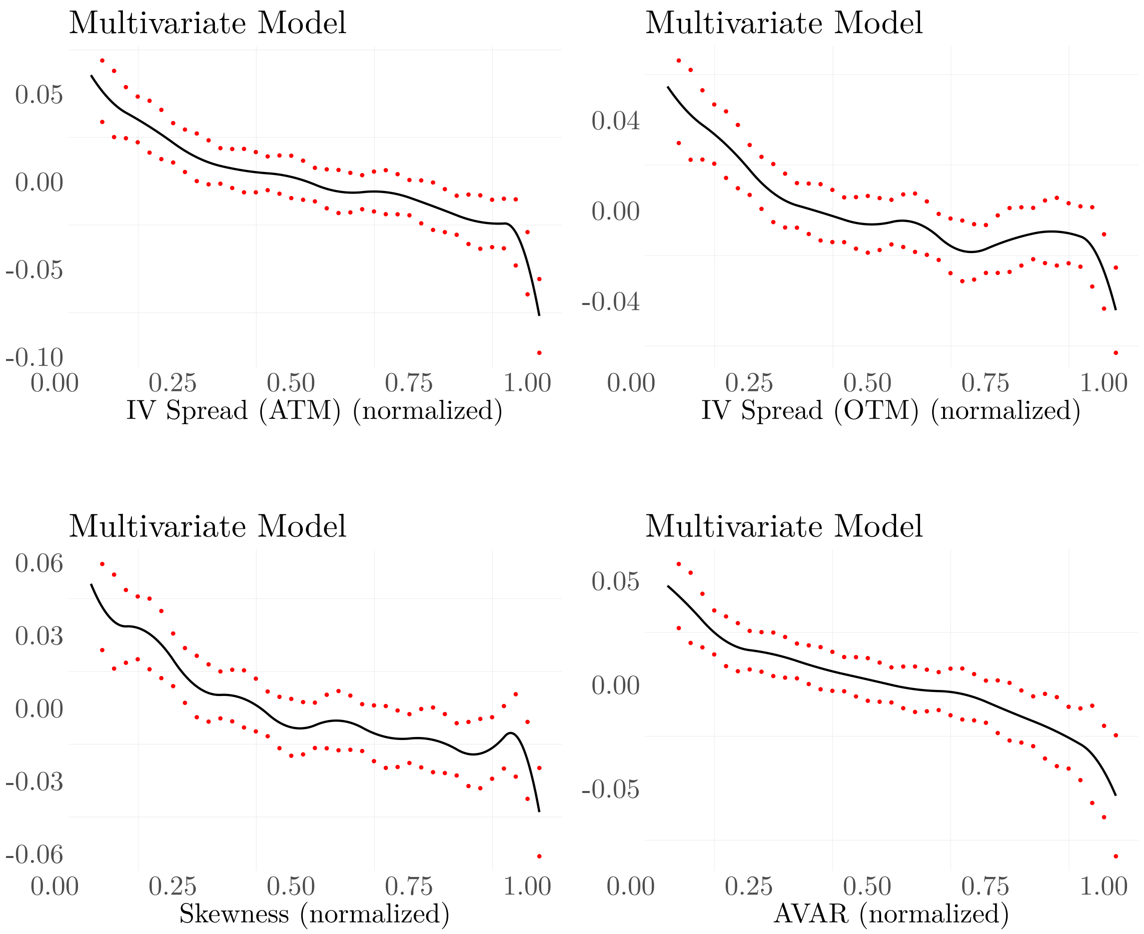
This figure shows the correlation between the option characteristics. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR$^+$ and VAR$^-$ denote the risk-neutral positive and negative semi-variances; VAR^Q denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and β_{Jump} denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2.

Figure 3: **Conditional Mean Functions - Selected vs. Not Selected Predictors**



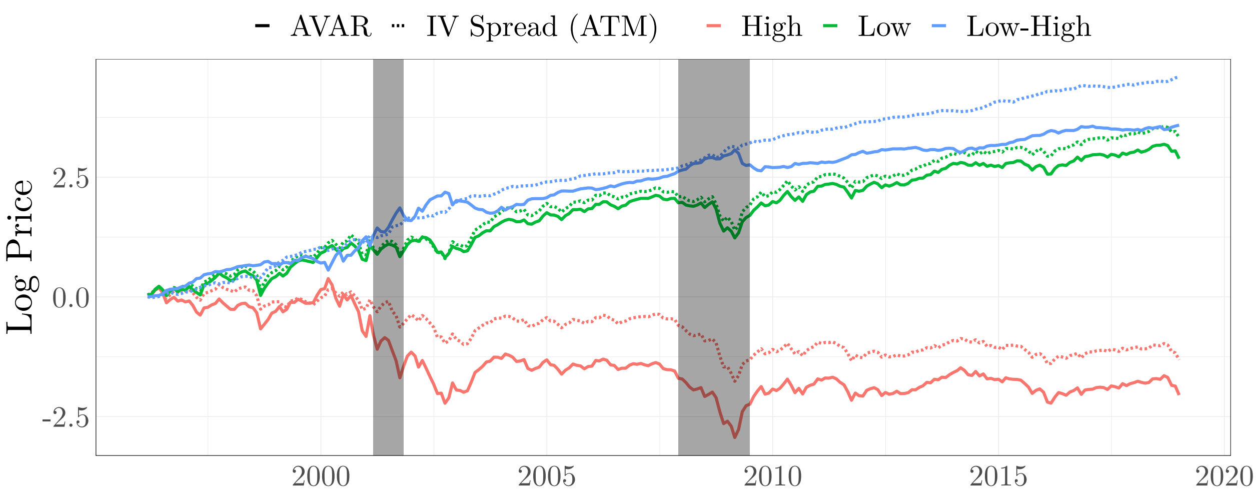
The upper panel of the figure shows the conditional mean function for the IV spread (ATM), one of the strongest predictors, in a univariate model (left) and a multivariate model (right). The multivariate model includes the variable itself as well as the additional predictors selected by the adaptive group LASSO. A complete overview the variables is provided in Table 5. The lower panel provides the corresponding plots for the volatility-of-volatility variable. Specifically, "Vol. of vol" shows some predictive ability in the univariate model, but is not selected by the adaptive group LASSO in the multivariate model. The red dots indicate pointwise 95% confidence bands.

Figure 4: **Conditional Mean Functions - Most Successful Predictors**



This figure shows the conditional mean functions for the four most successful option characteristics in their respective multivariate models. We have IV spread ATM in the upper left, IV spread (OTM) in the upper right, Skewness in the lower left and AVAR in the lower right. The multivariate model contains the option characteristic itself and all other variable selection by the adaptive group lasso. The red dots indicate pointwise 95% confidence bands.

Figure 5: **Cumulative Returns and NBER Recessions**



This plot shows the cumulative returns for two of the most successful option characteristics; risk-neutral variance asymmetry (AVAR) and the at-the-money (ATM) IV spread. The solid line depicts the cumulative returns of portfolio 1 and the dashed line depicts the cumulative returns for portfolio 10. The gray shaded area indicates NBER recessions. The sample period is 1996 through 2018.

Table 1: **Performance Statistics on High-Low Portfolios**

This table reports annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the maximum drawdown of the "10-1" portfolios. At the beginning of each calendar month, stocks are ranked according to the option characteristics and assigned to one of ten portfolios. The portfolio "10-1" is long the 10% stocks with highest values of the characteristic and short the 10% stocks with lowest values. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR^{+} and VAR^{-} denote the risk-neutral positive and negative semi-variances; VAR^{Q} denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and $\beta_{Vol.}$ denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. The sample period is 1996-2018.

	Mean (%)	Standard Deviation (%)	Sharpe Ratio	Low Pf. (%)	High Pf. (%)	Skewness	Kurtosis	Maximum Drawdown
CIV	-4.57	37.61	-0.12	8.83	4.26	0.56	3.48	82.63
PIV	-11.91	37.46	-0.32	10.63	-1.29	0.46	3.42	74.67
ΔCIV	8.25	12.34	0.67	2.61	10.86	1.16	8.85	22.60
ΔPIV	-4.91	12.01	-0.41	8.71	3.80	-0.93	13.20	37.99
O/S	-9.72	16.03	-0.61	13.97	4.25	-0.28	12.79	60.75
VRP	1.32	14.17	0.09	6.86	8.17	-0.26	1.26	52.46
IV Spread (ATM)	-20.67	9.99	-2.07	18.34	-2.33	-1.71	7.11	7.40
IV Spread (OTM)	-15.77	11.54	-1.37	17.78	2.01	-2.49	16.88	13.80
Skewness	-13.99	11.54	-1.21	16.44	2.45	-2.91	21.81	16.84
β_{Jump}	-1.56	10.86	-0.14	11.98	10.42	0.40	2.79	28.40
$\beta_{\mathrm{Vol.}}$	3.27	8.51	0.38	9.42	12.69	-0.02	2.46	19.47
AVAR	-17.43	18.35	-0.95	16.11	-1.32	0.06	4.91	35.60
VAR^{+}	-3.64	39.30	-0.09	9.41	5.76	0.87	5.42	89.60
VAR^{-}	-8.63	39.59	-0.22	10.85	2.22	0.85	5.44	80.65
VAR^{Q}	-6.22	40.06	-0.16	10.12	3.90	0.90	5.78	85.56
KT	-5.51	40.12	-0.14	10.11	4.60	0.94	5.93	87.61
vol-of-vol	-5.29	9.31	-0.57	11.93	6.64	0.31	3.82	26.87

Table 2: **FF6 Alphas - Portfolios Sorted on Option Characteristics**

This table reports alphas and factor loadings based on the Fama & French (2015) five factor model augmented with the momentum factor (Carhart 1997) for each of the "10-1" portfolios. At the beginning of each calendar month, stocks are ranked according the option characteristics and assigned to one of ten portfolios. The portfolio "10-1" is long the 10% stocks with highest values of the characteristic and short the 10% stocks with lowest values. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR^+ and VAR^- denote the risk-neutral positive and negative semi-variances; VAR^Q denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and $\beta_{Vol.}$ denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. Newey & West (1987) standard errors are given in parentheses. The sample period is 1996-2018.

Panel A:

	CIV	PIV	ΔCIV	ΔPIV	O/S	VRP	$\mathtt{IVS}_{\mathrm{ATM}}$	$\mathtt{IVS}_{\mathrm{OTM}}$	SKEW
(Intercept)	−0.02	−0.58*	0.61***	−0.38**	−0.82***	0.16	−1.80***	−1.39***	−1.26***
	(0.30)	(0.30)	(0.21)	(0.17)	(0.23)	(0.24)	(0.21)	(0.24)	(0.25)
mktrf	0.64***	0.60***	0.12**	0.05	0.14*	0.00	−0.04	−0.10	−0.07
	(0.10)	(0.10)	(0.06)	(0.05)	(0.08)	(0.09)	(0.06)	(0.07)	(0.08)
smb	1.11***	1.09***	0.09	0.07	−0.10	0.13	0.09	−0.06	−0.06
	(0.12)	(0.11)	(0.13)	(0.13)	(0.12)	(0.11)	(0.06)	(0.10)	(0.10)
hml	−0.40***	−0.38***	0.13	0.04	−0.41***	−0.17	0.22**	0.23***	0.22**
	(0.14)	(0.12)	(0.10)	(0.12)	(0.09)	(0.12)	(0.10)	(0.09)	(0.11)
rmw	−1.32***	−1.38***	0.07	−0.09	−0.39**	−0.08	−0.01	0.11	0.07
	(0.15)	(0.16)	(0.19)	(0.16)	(0.17)	(0.19)	(0.11)	(0.12)	(0.12)
cma	−0.59***	−0.60***	−0.21	−0.09	−0.23	0.05	−0.00	0.01	0.04
	(0.18)	(0.18)	(0.14)	(0.14)	(0.21)	(0.19)	(0.17)	(0.15)	(0.16)
umd	−0.66***	−0.67***	−0.02	−0.07	0.46***	−0.08	0.13*	0.17*	0.19**
	(0.10)	(0.10)	(0.05)	(0.05)	(0.12)	(0.10)	(0.07)	(0.09)	(0.08)
Adj. R^2	0.86	0.87	0.03	0.02	0.55	0.03	0.08	0.18	0.16
Num. obs.	275	275	274	274	275	275	275	275	275

Panel B:

	β_{Jump}	$\beta_{\mathrm{Vol.}}$	AVAR	VAR^+	VAR^-	$\mathrm{VAR}^{\mathbb{Q}}$	KT	VOV
(Intercept)	−0.06	0.30*	−1.05***	0.18	−0.22	−0.01	0.05	−0.22
	(0.17)	(0.16)	(0.22)	(0.36)	(0.37)	(0.38)	(0.38)	(0.18)
mktrf	0.10	−0.00	0.14*	0.57***	0.58***	0.57***	0.58***	−0.15***
	(0.07)	(0.04)	(0.08)	(0.11)	(0.12)	(0.12)	(0.12)	(0.05)
smb	0.05	−0.00	0.18*	1.16***	1.15***	1.17***	1.17***	0.06
	(0.07)	(0.05)	(0.10)	(0.13)	(0.13)	(0.13)	(0.13)	(0.08)
hml	0.04	0.09	−0.23**	−0.41***	−0.37***	−0.38***	−0.39***	0.09
	(0.10)	(0.09)	(0.10)	(0.12)	(0.13)	(0.13)	(0.13)	(0.07)
rmw	−0.38***	0.03	−0.91***	−1.38***	−1.41***	−1.41***	−1.41***	−0.16
	(0.12)	(0.09)	(0.14)	(0.16)	(0.15)	(0.16)	(0.16)	(0.11)
cma	0.09	−0.19	−0.24	−0.71***	−0.77***	−0.76***	−0.76***	−0.16
	(0.12)	(0.15)	(0.15)	(0.23)	(0.23)	(0.24)	(0.24)	(0.15)
umd	−0.07	−0.00	−0.29***	−0.76***	−0.77***	−0.80***	−0.80***	−0.16*
	(0.07)	(0.06)	(0.08)	(0.13)	(0.14)	(0.14)	(0.14)	(0.08)
Adj. R^2	0.21	−0.01	0.63	0.85	0.85	0.85	0.85	0.10
Num. obs.	272	272	275	275	275	275	275	275

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: **Alphas Against Alternative Factor Models**

This table reports alphas of the "10-1" portfolios for an extended set of factors. FF3 is the Fama & French (1993) three factor model, FF4 is the Fama-French three factor model augmented with the momentum factor of Carhart (1997), FF7a is the Fama & French (2015) five factor model augmented with momentum factor and the Pástor & Stambaugh (2003) liquidity factor, FF7b is the five factor model augmented with momentum and an idiosyncratic volatility factor, HXZ and HXZM is the investment model of Hou et al. (2015) with and without the momentum factor, SY is the Stambaugh & Yuan (2017) mispricing factor model; PC5 and PC10 takes the first five and ten asymptotic principal components (e,.g., Connor & Korajczyk (1986)) of characteristics sorted portfolios using the 62 characteristics of Freyberger et al. (2020); RP-PC5 and RP-PC10 are risk-premium principal components of Lettau & Pelger (2020b) extracted from the same sorted portfolios. At the beginning of each calendar month, stocks are ranked according the option characteristics and assigned to one of ten portfolios. The portfolio "10-1" is long the 10% stocks with highest values of the characteristic and short the 10% stocks with lowest values. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR^+ and VAR^- denote the risk-neutral positive and negative semi-variances; VAR^Q denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and $\beta_{Vol.}$ denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. Newey & West (1987) standard errors are given in parentheses. The sample period is 1996-2018.

	CAPM	FF3	FF4	FF7a	FF7b	HXZ	HXZM	SY	PC5	PC10	RP-PC5	RP-PC10
CIV	-1.32^{***}	-1.25^{***}	-0.75^{**}	-0.15	-0.08	0.01	0.02	0.26	-0.63^{*}	0.24	0.21	0.37
PIV	-1.93^{***}	-1.85^{***}	-1.35^{***}	-0.71^{**}	-0.63^{**}	-0.57	-0.56	-0.34	-1.24^{***}	-0.21	-0.20	-0.04
ΔCIV	0.60^{**}	0.59^{***}	0.60^{**}	0.62^{***}	0.52^{***}	0.63^{***}	0.63^{**}	0.65^{***}	0.57^{**}	-0.07	-0.29	-0.19
ΔPIV	-0.48^{***}	-0.49^{**}	-0.44^{**}	-0.35^{**}	-0.44^{***}	-0.42^{**}	-0.41^{**}	-0.38^{*}	-0.47^{***}	-0.55^{**}	-0.66^{**}	-0.55^{*}
O/S	-0.92^{***}	-0.75^{***}	-1.04^{***}	-0.85^{***}	-0.78^{***}	-0.84^{**}	-0.87^{***}	-1.17^{***}	-0.76^{***}	-0.26	-0.26	-0.17
VRP	0.06	0.08	0.14	0.19	0.10	0.30	0.30	0.33	0.11	-0.50^{*}	-0.29	-0.56^{*}
IV Spread (ATM)	-1.67^{***}	-1.71^{***}	-1.80^{***}	-1.77^{***}	-1.76^{***}	-1.91^{***}	-1.91^{***}	-1.94^{***}	-1.91^{***}	-1.25^{***}	-1.13^{***}	-1.09^{***}
IV Spread (OTM)	-1.18^{***}	-1.22^{***}	-1.34^{***}	-1.35^{***}	-1.34^{***}	-1.51^{***}	-1.51^{***}	-1.54^{***}	-1.41^{***}	-0.64^{***}	-0.52^{***}	-0.45^{**}
Skewness	-1.05^{***}	-1.09^{***}	-1.22^{***}	-1.23^{***}	-1.20^{***}	-1.37^{***}	-1.37^{***}	-1.46^{***}	-1.26^{***}	-0.49^{***}	-0.36^{**}	-0.30^{*}
β_{Jump}	-0.26	-0.27	-0.21	-0.08	-0.06	-0.02	-0.02	-0.03	-0.16	0.08	0.18	0.12
$\beta_{\text{Vol.}}$	0.27^{**}	0.26^{**}	0.27^{*}	0.29^{*}	0.30^{**}	0.28^{*}	0.28	0.29^{*}	0.19	-0.03	-0.09	-0.06
AVAR	-1.81^{***}	-1.74^{***}	-1.52^{***}	-1.11^{***}	-1.04^{***}	-1.07^{***}	-1.07^{***}	-1.12^{***}	-1.31^{***}	-0.71^{***}	-0.56^{**}	-0.58^{**}
VAR$^+$	-1.25^{**}	-1.17^{***}	-0.60	0.06	0.10	0.21	0.23	0.45	-0.51	0.10	-0.01	0.20
VAR$^-$	-1.68^{***}	-1.60^{***}	-1.03^{***}	-0.35	-0.29	-0.18	-0.17	0.05	-0.94^{***}	-0.18	-0.28	-0.05
VAR^Q	-1.49^{***}	-1.41^{***}	-0.82^{**}	-0.14	-0.08	0.03	0.04	0.28	-0.73^{**}	-0.01	-0.11	0.12
KT	-1.43^{***}	-1.35^{***}	-0.75^{*}	-0.08	-0.02	0.09	0.10	0.34	-0.66^{*}	0.02	-0.09	0.14
vol-of-vol	-0.43^{**}	-0.44^{**}	-0.33^{*}	-0.19	-0.24	-0.31	-0.30	-0.17	-0.41^{**}	-0.36	-0.44^{**}	-0.28

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: **Option Characteristic Spanning with $\mathbb{P}$-controls**

This table reports alphas and factor loadings of the "10-1" portfolios based on the Fama & French (2015) five factor model augmented with the momentum factor (Carhart (1997)) and five $\mathbb{P}$-tail sorted portfolios (Section 3.3): $\beta_{Downside}$ is the downside risk factor of Ang, Chen & Xing (2006), β_{Tail} is tail factor of Kelly & Jiang (2014), Max is max-factor of Bali et al. (2011), P-Skewness is a realized skewness factor of Amaya et al. (2015) and LF Risk is the low-frequency market risk factor of Neuhierl & Varneskov (2021). At the beginning of each calendar month, stocks are ranked according the option characteristics and assigned to one of ten portfolios. The portfolio "10-1" is long the 10% stocks with highest values of the characteristic and short the 10% stocks with lowest values. The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. Newey & West (1987) standard errors are given in parentheses. The sample period is 1996-2018.

Panel A:

	CIV	PIV	ΔCIV	ΔPIV	O/S	VRP	IVS_{ATM}	IVS_{OTM}	SKEW
(Intercept)	-0.02	-0.55^{**}	0.26^{*}	-0.55^{***}	-0.53^{***}	-0.19	-1.59^{***}	-1.07^{***}	-0.92^{***}
	(0.21)	(0.23)	(0.15)	(0.19)	(0.19)	(0.25)	(0.16)	(0.14)	(0.16)
mktrf	0.23^{**}	0.22^{**}	0.08^{*}	0.05	0.18^{**}	0.03	0.09	0.02	0.04
	(0.10)	(0.10)	(0.05)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)
smb	0.76^{***}	0.73^{***}	0.04	0.02	-0.11	0.07	0.15^{**}	0.05	0.07
	(0.07)	(0.07)	(0.12)	(0.14)	(0.09)	(0.08)	(0.06)	(0.07)	(0.07)
hml	-0.15^{*}	-0.11	0.11	0.04	-0.38^{***}	-0.20^{*}	0.20^{**}	0.19^{**}	0.19^{*}
	(0.08)	(0.08)	(0.12)	(0.11)	(0.08)	(0.11)	(0.09)	(0.09)	(0.10)
rmw	-0.57^{***}	-0.57^{***}	0.01	-0.10	-0.18	-0.18	-0.02	0.02	0.03
	(0.14)	(0.13)	(0.17)	(0.17)	(0.12)	(0.16)	(0.11)	(0.11)	(0.10)
cma	-0.31^{**}	-0.35^{***}	-0.06	-0.01	-0.38^{**}	0.20	-0.16	-0.18^{*}	-0.19^{*}
	(0.12)	(0.12)	(0.09)	(0.15)	(0.15)	(0.17)	(0.12)	(0.10)	(0.10)
umd	-0.32^{***}	-0.34^{***}	0.16^{**}	0.03	0.35^{***}	0.08	-0.02	-0.05	-0.05
	(0.08)	(0.07)	(0.06)	(0.09)	(0.07)	(0.08)	(0.04)	(0.04)	(0.05)
β_{Downside}	-0.43^{***}	-0.41^{***}	0.02	0.01	0.08	0.07	0.14^{**}	0.10^{*}	0.11^{**}
	(0.10)	(0.09)	(0.06)	(0.07)	(0.08)	(0.06)	(0.06)	(0.05)	(0.05)
β_{Tail}	-0.11	-0.11	0.03	0.07	-0.09	0.16^{***}	0.01	-0.01	-0.10
	(0.08)	(0.07)	(0.06)	(0.09)	(0.11)	(0.06)	(0.06)	(0.06)	(0.07)
Max	-0.29^{***}	-0.33^{***}	-0.06	-0.04	-0.14^{**}	-0.06	-0.02	0.07	0.05
	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.08)	(0.05)	(0.04)	(0.04)
P-Skewness	0.27^{**}	0.20^{*}	0.44^{***}	0.14	-0.23^{***}	0.28^{**}	-0.31^{***}	-0.39^{***}	-0.36^{***}
	(0.13)	(0.11)	(0.13)	(0.14)	(0.09)	(0.13)	(0.08)	(0.08)	(0.07)
LF Risk	0.08	0.09	0.07	0.08	-0.26^{***}	0.12	-0.13^{*}	-0.19^{**}	-0.18^{**}
	(0.11)	(0.09)	(0.06)	(0.09)	(0.09)	(0.11)	(0.08)	(0.07)	(0.07)
Adj. R^2	0.92	0.93	0.22	0.06	0.62	0.16	0.29	0.45	0.47
Num. obs.	275	275	274	274	275	275	275	275	275

Panel B:

	β_{Jump}	$\beta_{\text{Vol.}}$	AVAR	VAR^{+}	VAR^{-}	$VAR^{\mathbb{Q}}$	KT	VOV
(Intercept)	-0.01	0.25	-0.85^{***}	0.04	-0.31	-0.12	-0.07	-0.34^{*}
	(0.19)	(0.16)	(0.21)	(0.21)	(0.22)	(0.22)	(0.22)	(0.18)
mktrf	-0.02	0.05	-0.09	0.14^{**}	0.14^{*}	0.12^{*}	0.12^{*}	-0.14^{***}
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
smb	0.03	-0.07	0.01	0.73^{***}	0.69^{***}	0.71^{***}	0.72^{***}	0.06
	(0.07)	(0.05)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)
hml	0.12	0.09	-0.02	-0.15^{*}	-0.08	-0.10	-0.11	0.02
	(0.09)	(0.07)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.06)
rmw	-0.15	0.01	-0.32^{**}	-0.60^{***}	-0.54^{***}	-0.57^{***}	-0.57^{***}	-0.41^{***}
	(0.18)	(0.11)	(0.14)	(0.10)	(0.12)	(0.12)	(0.12)	(0.11)
cma	0.08	-0.14	-0.20	-0.32^{***}	-0.39^{***}	-0.36^{***}	-0.35^{***}	-0.05
	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
umd	-0.06	0.05	-0.20^{***}	-0.31^{***}	-0.32^{***}	-0.33^{***}	-0.33^{***}	-0.10
	(0.06)	(0.04)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)
β_{Downside}	-0.12	0.03	-0.31^{***}	-0.45^{***}	-0.48^{***}	-0.49^{***}	-0.49^{***}	0.00
	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.05)
β_{Tail}	-0.23^{***}	0.18^{***}	-0.21^{***}	-0.01	-0.01	-0.00	-0.01	0.21^{***}
	(0.06)	(0.04)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.05)
Max	-0.03	-0.04	-0.13^{**}	-0.36^{***}	-0.38^{***}	-0.37^{***}	-0.36^{***}	0.08^{**}
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
P-Skewness	0.11	-0.11^{**}	-0.07	0.37^{***}	0.30^{***}	0.34^{***}	0.35^{***}	0.06
	(0.08)	(0.05)	(0.07)	(0.08)	(0.09)	(0.10)	(0.09)	(0.05)
LF Risk	0.06	0.05	0.15^{**}	0.13^{*}	0.16^{**}	0.15^{**}	0.16^{**}	-0.02
	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
Adj. R^2	0.29	0.11	0.71	0.94	0.94	0.94	0.94	0.20
Num. obs.	272	272	275	275	275	275	275	275

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5: **Selected Predictors in Nonparametric Model**

This table reports the model selection results from the adaptive group LASSO outlined in Section 3.7. We employ the 62 characteristics from Freyberger et al. (2020) together with the four $\mathbb{P}$-tail measures as controls and then estimate the adaptive group LASSO, adding one option characteristic at a time. The first column of the table indicate which option characteristic is added to the model. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR^+ and VAR^- denote the risk-neutral positive and negative semi-variances; VAR^Q denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and $\beta_{Vol.}$ denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2.

	N	**Sample Period**			**Selected**	**All Selected Characteristics**
CIV	529360	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, Investment, LDP, NOA, PM adj, SUV, Total vol
PIV	529360	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, NOA, PM adj, SUV, Total vol, PIV
ΔCIV	523048	Mar 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, NOA, PM adj, SUV, Total vol, ΔCIV
ΔPIV	523048	Mar 1996	-	Dec 2018	N	Beta, ΔShrout, Investment, LDP, NOA, PM adj, SUV, Total vol, P-Skewness I
O/S	504520	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, ΔSo, LDP, NOA, O2P, PM adj, SUV, Total vol, O/S
VRP	534018	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, NOA, PM adj, SUV, Total vol
IV Spread (ATM)	500674	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, PM adj, SUV, Total vol, IV Spread (ATM)
IV Spread (OTM)	500674	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, PM adj, SUV, Total vol, IV Spread (OTM)
Skewness	534429	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, ΔSo, Investment, LDP, NOA, PM adj, PROF, SUV, Total vol, Skewness
β_{Jump}	1062012	May 1996	-	Dec 2018	N	Beta, r_{12-7}, r_{2-1}, ΔShrout, ΔSo, LDP, LME, Lturnover, NOA, PM adj, Rel to high price, SUV, Total vol, β_{Downside}, P-Skewness I
$\beta_{\text{Vol.}}$	1062012	May 1996	-	Dec 2018	N	Beta, r_{12-7}, r_{2-1}, ΔShrout, ΔSo, LDP, LME, Lturnover, NOA, PM adj, Rel to high price, SUV, Total vol, β_{Downside}, P-Skewness I
AVAR	534022	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, ΔSo, NOA, PM adj, PROF, SUV, Total vol, AVAR
VAR^+	534022	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, NOA, PM adj, SUV, Total vol
VAR^-	534022	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, NOA, PM adj, SUV, Total vol
VAR^Q	534022	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, NOA, PM adj, SUV, Total vol
KT	534022	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, NOA, PM adj, SUV, Total vol
vol-of-vol	533727	Feb 1996	-	Dec 2018	N	Beta, ΔShrout, ΔSo, Investment, LDP, NOA, PM adj, PROF, SUV, Total vol

Table 6: **Portfolios Characteristics for Option Characteristics**

This table shows the average portfolio characteristics for the ten sorted portfolios of each of the most successful option characteristics. Specifically, IV Spread (ATM) and IV Spread (OTM) are the differences between at-the-money and out-of-the-money implied volatilities, Skewness is risk-neutral skewness, and AVAR is variance asymmetry. The excess returns are reported in monthly percentages, LJI and RJI are the left- and right jump intensities of Bollerslev & Todorov (2014), Leverage is detailed in Section 4.3, ATM Volatility is the average between put- and call at-the-money implied volatility and Vol. of vol is volatility of volatility. The sample period is 1996-2018.

	Portfolio									
	1	2	3	4	5	6	7	8	9	10
Excess Return (%)										
IV Spread (ATM)	1.53	1.30	1.09	0.96	0.92	0.81	0.80	0.59	0.47	-0.19
IV Spread (OTM)	1.48	1.26	0.99	0.92	0.85	0.78	0.65	0.62	0.58	0.17
AVAR	1.34	1.15	1.03	1.02	0.95	0.88	0.86	0.71	0.47	-0.11
Skewness	1.37	1.23	1.02	0.95	0.86	0.82	0.71	0.60	0.50	0.20
Left Jump Intensity										
IV Spread (ATM)	0.79	0.81	0.80	0.79	0.79	0.79	0.81	0.83	0.87	0.98
IV Spread (OTM)	0.71	0.73	0.73	0.75	0.78	0.81	0.84	0.88	0.94	1.10
AVAR	0.77	0.78	0.77	0.77	0.78	0.80	0.82	0.86	0.90	1.03
Skewness	0.72	0.73	0.73	0.75	0.78	0.81	0.84	0.88	0.94	1.11
Right Jump Intensity										
IV Spread (ATM)	0.47	0.46	0.44	0.42	0.42	0.42	0.43	0.44	0.46	0.47
IV Spread (OTM)	0.45	0.43	0.41	0.41	0.41	0.43	0.44	0.46	0.48	0.52
AVAR	0.51	0.49	0.45	0.43	0.42	0.42	0.42	0.43	0.43	0.45
Skewness	0.49	0.44	0.41	0.41	0.41	0.42	0.43	0.45	0.47	0.51
Leverage										
IV Spread (ATM)	0.09	-0.26	-0.11	-0.18	-0.19	-0.22	-0.20	-0.26	-0.39	-0.08
IV Spread (OTM)	0.03	-0.03	-0.15	-0.15	-0.16	-0.46	-0.26	-0.40	-0.46	0.23
AVAR	0.58	-0.22	-0.08	-0.22	-0.18	-0.29	-0.31	-0.38	-0.34	-0.76
Skewness	0.20	-0.05	-0.15	-0.16	-0.34	-0.30	-0.27	-0.40	-0.35	0.15
ATM Volatility										
IV Spread (ATM)	0.65	0.50	0.44	0.41	0.40	0.41	0.42	0.45	0.51	0.66
IV Spread (OTM)	0.68	0.50	0.42	0.41	0.42	0.43	0.45	0.47	0.50	0.56
AVAR	0.63	0.40	0.35	0.34	0.36	0.39	0.44	0.51	0.61	0.85
Skewness	0.68	0.51	0.42	0.41	0.41	0.43	0.46	0.48	0.51	0.57
Vol. of vol										
IV Spread (ATM)	0.16	0.11	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.15
IV Spread (OTM)	0.15	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.12	0.16
AVAR	0.16	0.13	0.11	0.10	0.09	0.09	0.10	0.10	0.11	0.12
Skewness	0.16	0.11	0.09	0.09	0.09	0.09	0.10	0.11	0.12	0.16

Table 7: **Alphas Against Alternative Factor Models**

This table reports alphas for the "10-1" portfolios for most successful predictors (IV spread (ATM), IV spread (OTM), Skewness and AVAR) against an alternative factor model. Specifically, we include five risk-premium principal components of Lettau & Pelger (2020b) extracted from characteristic sorted portfolios using the 62 firm characteristics from Freyberger et al. (2020) together with the five $\mathbb{P}$-distribution controls: $\beta_{Downside}$ from Ang, Chen & Xing (2006), β_{Tail} of Kelly & Jiang (2014), Max is the max statistic from Bali et al. (2011), realized P-Skewness from Amaya et al. (2015) and the low-frequency market risk factor from Neuhierl & Varneskov (2021). In addition, we construct "high-low" portfolios from the structural option-based control variables: leverage, volatility of volatility, at-the-money volatility and the left tail jump intensity (LJI). The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. Newey & West (1987) standard errors are given in parentheses. The sample period is 1996-2018.

	IV Spread (ATM)	IV Spread (OTM)	Skewness	AVAR
Panel A: $\mathbb{Q}$-Controls				
(Intercept)	-1.13^{***}	-0.73^{***}	-0.49^{**}	-0.75^{***}
	(0.15)	(0.17)	(0.19)	(0.17)
Leverage	-0.54^{***}	-0.49^{***}	-0.56^{***}	-0.16^{**}
	(0.06)	(0.13)	(0.14)	(0.06)
Vol. of. Vol.	0.00	0.07	0.00	-0.10
	(0.09)	(0.08)	(0.08)	(0.06)
ATM Vol.	-0.04	-0.23^{***}	-0.24^{***}	0.16^{***}
	(0.03)	(0.03)	(0.03)	(0.04)
LJI	0.04	0.22^{***}	0.27^{***}	0.50^{***}
	(0.05)	(0.05)	(0.04)	(0.06)
Adj. R^2	0.34	0.47	0.52	0.80
Num. obs.	275	275	275	275
Panel B: $\mathbb{P} + \mathbb{Q}$-Controls				
(Intercept)	-1.12^{***}	-0.71^{***}	-0.48^{**}	-0.73^{***}
	(0.15)	(0.16)	(0.19)	(0.17)
Leverage	-0.50^{***}	-0.42^{***}	-0.47^{***}	-0.18^{***}
	(0.06)	(0.08)	(0.09)	(0.07)
Vol. of. Vol.	-0.03	0.06	0.02	-0.03
	(0.09)	(0.08)	(0.10)	(0.06)
ATM Vol.	0.03	-0.13^{***}	-0.13^{***}	0.14^{**}
	(0.05)	(0.05)	(0.04)	(0.06)
LJI	0.01	0.20^{***}	0.25^{***}	0.45^{***}
	(0.04)	(0.06)	(0.06)	(0.06)
LF Risk	-0.05	-0.13^{*}	-0.11^{*}	0.16^{***}
	(0.08)	(0.07)	(0.07)	(0.05)
Downside Beta	-0.08^{**}	-0.07	-0.08	0.09^{**}
	(0.04)	(0.05)	(0.05)	(0.04)
Tail Beta	0.01	-0.03	-0.08	-0.10^{*}
	(0.04)	(0.06)	(0.06)	(0.05)
P-Skewness	0.22^{*}	0.16	0.10	0.02
	(0.12)	(0.10)	(0.07)	(0.08)
Max-Stat	-0.04	-0.08	-0.08^{*}	-0.03
	(0.06)	(0.05)	(0.04)	(0.05)
Adj. R^2	0.36	0.49	0.55	0.81
Num. obs.	275	275	275	275

Panel C: $\mathbb{P} + \mathbb{Q}$ + RP-PC-Controls

(Intercept)	-0.82^{***}	-0.19	-0.05	-0.37^{*}
	(0.18)	(0.20)	(0.21)	(0.19)
Leverage	-0.37^{***}	-0.25^{***}	-0.31^{***}	-0.22^{***}
	(0.06)	(0.08)	(0.08)	(0.07)
Vol. of. Vol.	-0.06	0.01	-0.02	-0.06
	(0.08)	(0.07)	(0.08)	(0.06)
ATM Vol.	-0.06	-0.20^{***}	-0.19^{***}	0.18^{***}
	(0.06)	(0.06)	(0.06)	(0.06)
LJI	0.08	0.26^{***}	0.30^{***}	0.41^{***}
	(0.05)	(0.04)	(0.05)	(0.06)
LF Risk	-0.04	-0.05	-0.03	0.18^{***}
	(0.06)	(0.05)	(0.05)	(0.05)
Downside Beta	-0.08	-0.07	-0.09^{**}	0.11^{**}
	(0.05)	(0.04)	(0.04)	(0.05)
Tail Beta	0.08	0.07	0.01	-0.12^{**}
	(0.05)	(0.04)	(0.04)	(0.06)
P-Skewness	0.16	0.05	-0.01	0.08
	(0.12)	(0.10)	(0.08)	(0.08)
Max-Stat	0.01	0.14^{*}	0.17^{***}	0.02
	(0.09)	(0.08)	(0.06)	(0.07)
Adj. R^2	0.41	0.59	0.64	0.82
Num. obs.	275	275	275	275
RP-Control.	✓	✓	✓	✓

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 8: **Conditional Portfolio Sorts on SYY Mispricing Score**

This table shows annual percentage returns of conditional double sorts of the most successful option characteristics (IV spread (ATM), IV spread (OTM), Skewness and AVAR) and the Stambaugh et al. (2015) and Stambaugh & Yuan (2017) mispricing score. Stocks are first assigned to a low, medium and high category based on the SYY mispricing score and then sorted into 10 portfolios within each category based on the value of a given option characteristic in each month. All portfolios are equal weighted and rebalanced each month. The sample period is 1996-2016.

	Portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
Unconditional											
IV Spread (ATM)	20.12	16.21	12.96	12.87	11.85	9.79	10.07	7.63	6.91	1.95	-18.17
IV Spread (OTM)	18.53	15.44	12.58	11.86	10.66	10.45	8.74	8.53	9.56	4.02	-14.50
AVAR	18.31	14.17	13.71	12.29	12.21	11.30	11.50	9.35	7.81	0.61	-17.69
Skewness	18.40	14.80	13.20	11.80	10.82	10.51	9.55	8.73	8.35	4.94	-13.46
Low SYY Bin											
IV Spread (ATM)	22.16	17.35	13.31	14.71	13.92	12.83	10.41	10.86	9.37	8.33	-13.83
IV Spread (OTM)	21.56	16.29	12.57	12.56	12.40	10.65	13.38	11.26	11.29	11.27	-10.29
AVAR	21.35	15.35	13.73	13.18	12.34	13.64	11.60	12.61	11.37	9.78	-11.57
Skewness	19.93	17.54	13.38	12.00	12.63	12.35	12.18	11.92	10.73	12.33	-7.60
Medium SYY Bin											
IV Spread (ATM)	22.85	18.11	13.72	13.99	12.53	12.30	12.40	11.58	9.01	6.44	-16.41
IV Spread (OTM)	21.23	17.26	13.75	13.08	12.96	11.71	9.91	11.26	11.89	9.91	-11.32
AVAR	19.86	15.06	13.56	12.75	12.56	11.40	14.49	12.04	13.67	9.72	-10.14
Skewness	20.71	16.52	15.20	12.45	12.07	14.30	10.56	9.76	13.20	10.37	-10.34
High SYY Bin											
IV Spread (ATM)	17.46	11.36	11.12	8.99	7.56	6.06	2.46	2.71	1.93	-5.19	-22.66
IV Spread (OTM)	13.85	12.24	9.07	8.59	7.47	4.62	4.27	5.20	4.47	-5.21	-19.06
AVAR	14.42	12.31	13.15	10.63	8.17	7.05	3.68	4.03	-0.98	-6.85	-21.27
Skewness	15.42	9.28	9.37	10.73	6.98	3.82	6.90	4.51	2.95	-4.93	-20.35

Table 9: **Conditional Portfolio Sorts on Liquidity**

This table shows annual percentage returns of conditional double sorts of the most successful option characteristics (IV spread (ATM), IV spread (OTM), Skewness and AVAR) and the Corwin & Schultz (2012) liquidity measure. Stocks are first assigned to a low, medium and high category based on their liquidity and then sorted into 10 portfolios within each category based on the value of a given option characteristic in each month. All portfolios are equal weighted and rebalanced each month. The sample period is 1996-2018.

	Portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
Unconditional											
IV Spread (ATM)	18.22	15.59	13.05	11.61	10.95	9.93	9.59	7.15	5.50	-2.24	-20.45
IV Spread (OTM)	17.74	14.90	11.91	11.06	10.25	9.29	7.74	7.50	6.84	2.11	-15.63
AVAR	16.06	13.57	12.51	12.30	11.37	10.44	10.39	8.55	5.70	-1.16	-17.22
Skewness	16.30	14.95	12.03	11.49	10.21	9.89	8.41	7.42	5.91	2.52	-13.77
Low Liquidity Bin											
IV Spread (ATM)	15.09	13.52	13.71	9.42	7.92	6.69	2.01	0.95	-0.97	-16.88	-31.97
IV Spread (OTM)	12.20	13.37	14.05	3.41	9.43	2.94	6.53	0.84	0.58	-12.00	-24.20
AVAR	12.51	15.32	9.65	8.03	11.19	4.56	5.42	1.50	0.47	-13.20	-25.71
Skewness	14.31	10.19	8.17	12.10	9.49	5.10	5.61	0.00	0.80	-12.78	-27.09
Medium Liquidity Bin											
IV Spread (ATM)	19.15	14.65	13.14	10.26	10.68	12.52	10.96	5.63	7.11	0.86	-18.29
IV Spread (OTM)	17.20	14.30	13.53	11.19	10.83	8.28	7.61	9.11	10.22	2.66	-14.54
AVAR	17.16	12.96	12.03	11.64	10.00	10.69	7.56	10.92	7.13	2.45	-14.71
Skewness	15.64	13.76	10.69	11.37	11.31	9.23	9.91	9.37	8.08	2.81	-12.83
High Liquidity Bin											
IV Spread (ATM)	16.40	12.34	13.39	10.89	11.42	10.20	9.23	9.56	8.63	5.52	-10.88
IV Spread (OTM)	15.83	13.18	11.15	10.02	10.21	10.15	10.15	9.09	9.80	8.00	-7.83
AVAR	15.81	11.30	11.38	11.26	10.80	10.96	10.55	10.47	8.81	7.99	-7.82
Skewness	15.52	13.54	12.25	9.99	10.80	9.90	10.95	8.29	8.67	9.36	-6.16

Table 10: **Conditional Portfolio Sorts on Idiosyncratic Volatility**

This table shows annual percentage returns of conditional double sorts of the most successful option characteristics (IV spread (ATM), IV spread (OTM), Skewness and AVAR) and the idiosyncratic volatility. Stocks are first assigned to a low, medium and high category based on their idiosyncratic volatility and then sorted into 10 portfolios within each category based on the value of a given option characteristic in each month. All portfolios are equal weighted and rebalanced each month. Idiosyncratic volatility is relative to the Fama & French (1993) three-factor model. The sample period is 1996-2018.

	Portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
Unconditional											
IV Spread (ATM)	18.20	16.04	13.12	11.70	10.74	9.71	9.48	7.18	5.50	-2.07	-20.27
IV Spread (OTM)	17.79	15.07	12.01	10.91	10.20	9.42	7.61	7.06	7.34	2.17	-15.62
AVAR	16.09	13.76	12.47	12.17	11.44	10.46	10.24	8.08	6.29	-0.50	-16.60
Skewness	16.48	15.05	12.32	11.60	10.01	9.84	8.15	7.72	6.10	2.64	-13.83
Low Idiosyncratic Volatility Bin											
IV Spread (ATM)	18.90	14.22	14.00	12.81	11.17	11.13	10.20	10.74	8.82	7.80	-11.10
IV Spread (OTM)	17.42	14.99	12.27	11.51	10.99	10.51	11.45	10.69	10.46	9.53	-7.89
AVAR	17.16	13.71	12.47	12.28	11.91	11.42	11.77	10.87	10.63	9.70	-7.46
Skewness	17.37	14.72	13.36	11.20	11.32	11.34	11.95	10.14	9.83	10.65	-6.72
Medium Idiosyncratic Volatility Bin											
IV Spread (ATM)	20.76	17.68	13.29	14.39	11.15	10.73	9.93	7.47	5.10	0.21	-20.54
IV Spread (OTM)	20.67	17.84	13.81	10.80	10.89	8.75	9.39	7.21	6.74	4.56	-16.11
AVAR	21.12	14.35	13.31	11.22	12.27	10.34	8.73	10.25	6.87	2.94	-18.17
Skewness	20.53	16.35	12.94	12.91	10.34	9.90	8.86	8.72	6.81	3.80	-16.73
High Idiosyncratic Volatility Bin											
IV Spread (ATM)	14.90	10.43	13.66	7.78	5.45	6.74	5.43	3.28	-3.31	-12.24	-27.15
IV Spread (OTM)	12.17	11.86	10.11	7.77	9.55	6.73	1.42	5.27	0.51	-13.09	-25.25
AVAR	12.55	11.03	11.34	6.60	8.79	7.78	3.19	1.09	1.95	-10.48	-23.03
Skewness	11.33	9.13	12.64	8.51	8.56	3.90	6.15	2.99	1.40	-13.00	-24.33

Table 11: **Performance Statistics on High-Low Portfolios - S&P 500 Stocks**

This table reports annualized percentage means, annualized percentage standard deviations, annualized Sharpe ratios, skewness, kurtosis, the maximum drawdown, and the best- and worst-month returns of the "5-1" portfolios. At the beginning of each calendar month, stocks are ranked according the option characteristics and assigned to one of five portfolios, requiring that the stock is a member of the S&P 500 at the time of portfolio formation. The portfolio "5-1" is then long the 20% stocks with highest values of the characteristic and short the 20% stocks with lowest values. CIV and PIV denote at-the-money call and put implied volatility; ΔCIV and ΔPIV denote (time series) changes in call and put implied volatility; Skewness is a risk-neutral IV skewness measure; O/S is the stock-to-option trading volume (Johnson & So 2012); IV Spread (ATM) and IV Spread (OTM) are differences between at-the-money and out-of-the-money implied volatilities; AVAR is variance asymmetry, VAR^{+} and VAR^{-} denote the risk-neutral positive and negative semi-variances; VAR^{Q} denotes risk-neutral variance; VRP is the variance risk premium; β_{Jump} and $\beta_{Vol.}$ denote the jump and volatility betas of Cremers et al. (2015); KT is the Kadan & Tang (2020) bound; finally, Vol. of. Vol. is the volatility of implied volatility. The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. The sample period is 1996-2018.

	Mean (%)	Standard Deviation (%)	Sharpe Ratio	Low Pf. (%)	High Pf. (%)	Skewness	Kurtosis	Maximum Drawdown
CIV	3.92	25.71	0.15	8.81	12.73	0.77	3.95	72.44
PIV	2.31	25.66	0.09	9.76	12.07	0.74	3.83	76.24
ΔCIV	3.41	11.06	0.31	9.08	12.49	1.31	6.98	28.17
ΔPIV	0.25	11.25	0.02	11.11	11.37	1.12	9.04	38.61
O/S	-3.80	12.49	-0.30	13.42	9.62	0.06	4.66	60.88
VRP	5.10	11.58	0.44	10.05	15.14	0.52	9.72	26.94
IV Spread (ATM)	-5.10	6.79	-0.75	14.64	9.54	-0.85	4.77	15.01
IV Spread (OTM)	-5.40	8.29	-0.65	14.67	9.27	-0.19	2.85	22.76
Skewness	-4.51	9.43	-0.48	14.42	9.91	-0.12	3.26	28.15
β_{Jump}	0.78	13.02	0.06	10.88	11.66	1.30	5.94	58.54
$\beta_{\text{Vol.}}$	-1.02	11.49	-0.09	11.62	10.61	-1.47	10.75	42.92
AVAR	-2.42	19.42	-0.12	13.24	10.82	1.02	7.04	63.65
VAR^{+}	4.75	26.04	0.18	8.55	13.30	0.71	3.48	72.17
VAR^{-}	3.47	25.98	0.13	9.35	12.82	0.63	3.24	75.98
VAR^{Q}	4.09	26.09	0.16	8.97	13.06	0.68	3.21	73.79
KT	4.12	26.21	0.16	9.01	13.13	0.66	3.22	73.89
Vol. of. vol.	-1.96	8.28	-0.24	12.19	10.23	-0.74	5.31	33.15

Table 12: **Alphas Against Alternative Factor Models for S&P 500 Stocks**

This table reports alphas for the "5-1" portfolios for most successful predictors (IV spread (ATM), IV spread (OTM), Skewness and AVAR) against an alternative factor model. Specifically, we include five risk-premium principal components of Lettau & Pelger (2020b) extracted from characteristic sorted portfolios using the 62 firm characteristics from Freyberger et al. (2020) together with the five $\mathbb{P}$-distribution controls: $\beta_{Downside}$ from Ang, Chen & Xing (2006), β_{Tail} of Kelly & Jiang (2014), Max is the max statistic from Bali et al. (2011), realized P-Skewness from Amaya et al. (2015) and the low-frequency market risk factor from Neuhierl & Varneskov (2021). In addition, we construct "high-low" portfolios from the structural option-based control variables: leverage, volatility of volatility, at-the-money volatility and the left tail jump intensity (LJI). The option characteristics are described in detail in Section 3.2. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. Newey & West (1987) standard errors are given in parentheses. The sample period is 1996-2018.

	IV Spread (ATM)	IV Spread (OTM)	Skewness	AVAR
Panel A: $\mathbb{Q}$-Controls				
(Intercept)	−0.16	−0.01	0.09	0.20
	(0.12)	(0.14)	(0.13)	(0.26)
Leverage	−0.26***	−0.22***	−0.22***	−0.21**
	(0.04)	(0.07)	(0.07)	(0.10)
Vol. of. Vol.	0.03	0.15*	0.10	−0.25**
	(0.04)	(0.08)	(0.09)	(0.13)
ATM Vol.	−0.02	0.04	0.06	0.41***
	(0.02)	(0.04)	(0.04)	(0.08)
LJI	−0.03	0.11	0.15	−0.03
	(0.04)	(0.08)	(0.09)	(0.18)
Adj. R^2	0.22	0.23	0.31	0.54
Num. obs.	275	275	275	275
Panel B: $\mathbb{P} + \mathbb{Q}$-Controls				
(Intercept)	−0.18	−0.02	0.09	0.20
	(0.11)	(0.11)	(0.11)	(0.20)
Leverage	−0.23***	−0.24***	−0.24***	−0.33***
	(0.04)	(0.06)	(0.06)	(0.11)
Vol. of. Vol.	−0.01	0.10**	0.06	−0.22*
	(0.04)	(0.05)	(0.06)	(0.12)
ATM Vol.	0.04	0.05	0.06	0.28***
	(0.03)	(0.04)	(0.05)	(0.09)
LJI	−0.02	0.19***	0.22***	0.04
	(0.04)	(0.07)	(0.07)	(0.15)
LF Risk	−0.06	−0.14**	−0.12*	0.11
	(0.06)	(0.06)	(0.06)	(0.09)
Downside Beta	−0.09**	0.01	0.04	0.21**
	(0.04)	(0.05)	(0.06)	(0.10)
Tail Beta	0.03	0.11**	0.11**	0.04
	(0.03)	(0.04)	(0.04)	(0.15)
P-Skewness	0.08	−0.14*	−0.12	−0.40***
	(0.07)	(0.08)	(0.08)	(0.09)
Max-Stat	−0.03	−0.04	−0.06	0.01
	(0.03)	(0.03)	(0.04)	(0.08)
Adj. R^2	0.24	0.34	0.39	0.58
Num. obs.	275	275	275	275

Panel C: $\mathbb{P} + \mathbb{Q}$ + RP-PC-Controls

(Intercept)	-0.26^{*}	-0.13	0.08	0.33
	(0.15)	(0.15)	(0.18)	(0.27)
Leverage	-0.17^{***}	-0.19^{***}	-0.19^{***}	-0.29^{***}
	(0.05)	(0.05)	(0.06)	(0.08)
Vol. of. Vol.	-0.01	0.07^{*}	0.02	-0.30^{***}
	(0.04)	(0.04)	(0.05)	(0.09)
ATM Vol.	0.01	0.01	0.02	0.20^{**}
	(0.04)	(0.04)	(0.06)	(0.09)
LJI	0.02	0.23^{***}	0.26^{***}	0.10
	(0.03)	(0.05)	(0.06)	(0.08)
LF Risk	-0.09^{*}	-0.18^{***}	-0.16^{***}	0.04
	(0.05)	(0.05)	(0.06)	(0.08)
Downside Beta	-0.08^{*}	0.00	0.04	0.18^{**}
	(0.04)	(0.04)	(0.05)	(0.08)
Tail Beta	0.02	-0.00	0.01	-0.22^{**}
	(0.03)	(0.04)	(0.04)	(0.10)
P-Skewness	0.08	-0.01	-0.00	-0.07
	(0.07)	(0.08)	(0.09)	(0.09)
Max-Stat	-0.06	-0.05	-0.08	-0.05
	(0.05)	(0.06)	(0.06)	(0.11)
Adj. R^2	0.26	0.46	0.49	0.72
Num. obs.	275	275	275	275
RP-Control.	✓	✓	✓	✓

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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A Nonparametric Tail Estimates

We control for tail, or jump, variation in the option characteristics using the semi-nonparametric approach developed by Bollerslev & Todorov (2014) and Bollerslev et al. (2015). Specifically, they assume that the jump component of the price process (5) belongs to a flexible class of Lévy processes with,

$$\nu_t^{\mathbb{Q}}(dx) = \left(\phi_t^+ \times e^{-a_t^+ x}\mathbf{1}_{\{x>0\}} + \phi_t^- \times e^{-a_t^-|x|}\mathbf{1}_{\{x<0\}}\right)dx, \tag{A.1}$$

where $\phi_t^\pm$ and $a_t^\pm$ control the "level shifts" and shape of the jump distribution, respectively, which are allowed to be asymmetric for positive and negative jumps. Whereas this specification imposes an exponential structure (hence, the "semi" label) on the compensator, it nests many parametric models typically employed in the empirical option pricing literature. Importantly, we can consistently estimate the parameters of the compensator, starting with $a_t^\pm$, via the objective function,

$$\hat{a}_t^\pm = \underset{a^\pm}{\operatorname{argmin}} \frac{1}{N_t^\pm} \sum_{i=1}^{N_t^\pm} \left| \frac{\ln(O_{t,\tau}(k_{t,i})/O_{t,\tau}(k_{t,i-1}))}{k_{t,i} - k_{t,i-1}} - (1 \pm (-a^\pm)) \right|, \tag{A.2}$$

where $N_t^\pm$ is the number of OTM call (put) options used in the estimation with moneyness $0 < k_{t,1} < \ldots < k_{t,N_t^+}$ (equivalently, $0 < -k_{t,1} < \ldots < -k_{t,N_t^+}$). Recall, $k < 0$ indicates the log-moneyness of an OTM put option. Once we have obtained an estimate of $\hat{a}_t^\pm$, we can estimate $\phi_t^\pm$ since the former impose no restrictions on the latter. Hence, in a second step, we obtain,

$$\hat{\phi}_t^\pm = \underset{\phi^\pm}{\operatorname{argmin}} \frac{1}{N_t^\pm} \sum_{i=1}^{N_t^\pm} \left| \ln\left(\frac{e^{r_{t,\tau}} O_{t,\tau}(k_{t,i})}{\tau F_{t-,\tau}}\right) - (1 \mp \hat{a}_t^\pm)k_{t,i} + \ln(\hat{a}_t^\pm \mp 1) + \ln(\hat{a}_t^\pm) - \ln(\phi^\pm) \right|, \tag{A.3}$$

where, again, $F_{t-,\tau}$ is the implied futures price and $r_{t,\tau}$ is the risk-free rate.

Whereas $\hat{a}_t^\pm$ and $\hat{\phi}_t^\pm$ can, in principle, be estimated using a single option cross-section on a given trading day, we pool daily cross-sections across the preceeding month to reduce estimation errors. Specifically, suppose we have n_t days in month t, then we construct the shape estimates as

$$\hat{a}_t^\pm = \underset{a^\pm}{\operatorname{argmin}} \frac{1}{n_t} \sum_{j=t-n_t+1}^{t} \frac{1}{N_j^\pm} \sum_{i=1}^{N_j^\pm} \left| \frac{\ln(O_{j,\tau}(k_{j,i})/O_{j,\tau}(k_{j,i-1}))}{k_{j,i} - k_{j,i-1}} - (1 \pm (-a^\pm)) \right|,$$

and, similarly, for the level shift parameters,

$$\hat{\phi}_t^\pm = \underset{\phi^\pm}{\operatorname{argmin}} \frac{1}{n_t} \sum_{j=t-n_t+1}^{t} \frac{1}{N_j^\pm} \sum_{i=1}^{N_j^\pm} \left| \ln\left(\frac{e^{r_{j,\tau}} O_{j,\tau}(k_{j,i})}{\tau F_{j-,\tau}}\right) - (1 \mp \hat{a}_t^\pm)k_{j,i} + \ln(\hat{a}_t^\pm \mp 1) + \ln(\hat{a}_t^\pm) - \ln(\phi^\pm) \right|.$$

To this end, we employ options with a fixed one-month maturity and set the upper and lower parameter bounds for the numerical routines to 1000 and 0.00001, respectively.

Finally, once we have $\hat{a}_t^{\pm}$ and $\hat{\phi}_t^{\pm}$, we compute the left and right jump intensity as,

$$\texttt{LJI}_t = \int_{x<-|k_t|} \hat{\nu}_t^{\mathbb{Q}}(dx) = \hat{\phi}_t^- e^{-\hat{a}_t^-|k_t|}/\hat{a}_t^-, \quad \texttt{RJI}_t = \int_{x>|k_t|} \hat{\nu}_t^{\mathbb{Q}}(dx) = \hat{\phi}_t^+ e^{-\hat{a}_t^+|k_t|}/\hat{a}_t^+, \tag{A.4}$$

for some sensible log-moneyness cutoff k_t. Specifically, we implement the time-varying cutoff at two standard deviations from ATM, measured by the normalized at-the-money IV (and using the average of put and call IV). That is, since $k = \ln(1) = 0$ corresponds to ATM, we consider $k_t = \ln((1 + 2 \times \texttt{IV}_{\text{ATM}}\sqrt{\tau}))$, since $\texttt{IV}_{\text{ATM}}$ is annualized and $\tau = 1/12$ corresponds to one month.

B Supplementary Empirical Results

This section collects additional tables to complement the empirical analysis in the main text. Specifically, Table B.1 provides performance statistics for portfolios sorted based on the $\mathbb{P}$-distribution controls in Section 3.3 and the option-based controls in Section 4.2, both for the full cross-section of stocks (Panel A) and the S&P 500 subset of stocks (Panel B). Table B.2 shows the high-minus-low return spread as a function of the number of portfolios included in standard portfolio sorts for all option characteristics. Table B.3 reports the model selection results from the AG-LASSO exercise with option-based controls, $\mathbb{P}$-distribution controls and firm characteristics. Finally, Table B.4 provides conditional double sorts with size and the successful option characteristics.

Table B.1: **Performance Statistics for High-Low Portfolios of $\mathbb{P}$ and $\mathbb{Q}$ Controls**

This table reports annualized percentage means and standard deviations, annualized Sharpe ratios, skewness, kurtosis, the maximum drawdown, and the best- and worst-month returns of the "10-1" portfolios (Panel A) or "5-1" portfolios (Panel B). At the beginning of each calendar month, stocks are ranked according the predictors and assigned to one of the ten (five) portfolios. The portfolio "10-1" ("5-1") is then long the 10% (20%) stocks with highest values of the predictor and short the 10% (20%) stocks with lowest values. $\beta_{Downside}$ is the downside beta of Ang, Chen & Xing (2006), β_{Tail} is tail factor of Kelly & Jiang (2014), Max is max-factor of Bali et al. (2011), P-Skewness is a realized skewness factor of Amaya et al. (2015) and β_{LF} is the low-frequency market risk factor of Neuhierl & Varneskov (2021), LJI and RJI are the left- and right jump intensities of Bollerslev & Todorov (2014) and Leverage is detailed in Section 4.3. All stocks are equally weighted within a portfolio. Portfolios are rebalanced every month. The sample period is 1996-2018.

Panel A: All Stocks

	Mean (%)	Standard Deviation (%)	Sharpe Ratio	Low Pf. (%)	High Pf. (%)	Skewness	Kurtosis	Maximum Drawdown
β_{tail}	5.24	16.52	0.32	11.68	16.92	2.11	20.16	42.09
β_{Downside}	-5.86	26.92	-0.22	18.80	10.02	0.49	3.71	66.66
β_{LF}	3.62	10.18	0.36	12.39	16.00	1.56	9.85	27.24
Max-Stat	-5.91	30.08	-0.20	16.85	7.96	1.39	7.44	83.27
P-Skewness I	-8.60	13.65	-0.63	19.73	8.25	-1.92	24.41	34.37
LJI	-10.71	22.68	-0.47	12.66	1.95	0.22	9.16	47.40
RJI	1.02	10.97	0.09	9.60	10.62	2.36	19.45	40.24
Leverage	13.11	10.33	1.27	4.71	17.82	2.77	25.52	17.31

Panel B: S&P 500 Stocks

	Mean (%)	Standard Deviation (%)	Sharpe Ratio	Low Pf. (%)	High Pf. (%)	Skewness	Kurtosis	Maximum Drawdown
β_{tail}	3.06	11.77	0.26	10.88	13.94	2.28	14.61	43.65
β_{Downside}	2.48	23.17	0.11	9.57	12.06	0.01	2.46	77.12
β_{LF}	1.63	11.77	0.14	10.71	12.34	1.14	9.33	34.15
Max-Stat	-0.72	20.16	-0.04	11.97	11.25	0.71	5.62	64.31
P-Skewness I	-4.92	10.14	-0.49	13.63	8.71	-0.85	2.57	12.69
LJI	0.03	15.49	0.00	11.67	11.70	0.65	6.98	70.33
RJI	4.90	10.50	0.47	8.82	13.71	2.79	16.54	16.41
Leverage	0.67	9.11	0.07	11.52	12.19	-1.34	13.83	39.54

Table B.2: **High-Low Returns for Different Number of Sorting Portfolios**

This table shows the annualized returns of the "high-low" portfolio for the option characteristics for different numbers of sorting portfolios. For the first column, we see the annualized returns if we sort stocks into (only) two portfolios based on the option characteristics. In the second column, we see the results for five portfolios, the return thus corresponds to the "5-1" portfolio. For the next column it is the returns of the "10-1" portfolio and so on. Portfolio sorts are monthly and all portfolios are equal weighted. The sample period is 1996-2018.

	Ann. High-Low Return (%)					
	2	5	10	15	25	30
CIV	-2.28	-4.19	-4.57	-5.26	-6.24	-5.75
PIV	-3.91	-8.38	-11.91	-14.46	-16.74	-18.17
ΔCIV	4.07	7.53	8.25	8.37	8.09	8.79
ΔPIV	-1.18	-2.76	-4.91	-5.34	-8.10	-8.03
O/S	-4.94	-7.52	-9.72	-9.62	-9.02	-8.87
VRP	1.21	1.88	1.32	0.04	-0.08	-0.05
IV Spread (ATM)	-7.98	-15.32	-20.67	-23.24	-27.20	-27.65
IV Spread (OTM)	-6.49	-11.95	-15.77	-16.22	-17.86	-19.62
Skewness	-6.22	-11.41	-13.99	-14.91	-18.13	-19.73
β_{Jump}	0.32	-0.05	-1.56	-1.24	-0.51	-0.62
$\beta_{\text{Vol.}}$	0.31	1.29	3.27	4.50	4.62	4.30
AVAR	-6.44	-12.78	-17.43	-19.66	-21.66	-22.22
VAR$^+$	-2.57	-4.84	-3.64	-4.63	-5.79	-5.90
VAR$^-$	-3.66	-7.07	-8.63	-9.85	-10.62	-11.18
VAR^Q	-3.06	-6.21	-6.22	-6.84	-7.06	-8.08
KT	-2.91	-5.73	-5.51	-6.00	-7.29	-7.17
vol-of-vol	-2.80	-3.77	-5.29	-5.23	-5.40	-5.58

Table B.3: **Selected Predictors in Nonparametric Model (with $\mathbb{P}$ and $\mathbb{Q}$ controls)**

This table reports the model selection results from the adaptive group LASSO outlined in Section 3.7. Alongside the successful option characteristics, we include the 62 firm characteristics from Freyberger et al. (2020), the five $\mathbb{P}$-distribution controls and the structural option-based control variables in Section 4.2. The first column of the table indicates which option characteristics is added to the model. IV Spread (ATM) and IV Spread (OTM) are the differences between at-the-money and out-of-the-money implied volatilities, AVAR is variance asymmetry and Skewness is risk neutral skewness. The option characteristics are described in detail in Section 3.2.

	N	**Sample Period**			**Selected**	**All Selected Characteristics**
IV Spread (ATM)	500398	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, PM adj, SUV, Total vol, IV Spread (ATM)
IV Spread (OTM)	500398	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, Investment, LDP, PM adj, SUV, Total vol, IV Spread (OTM)
Skewness	533110	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, ΔSo, Investment, LDP, NOA, PM adj, PROF, SUV, Total vol, Skewness
AVAR	532744	Feb 1996	-	Dec 2018	Y	Beta, ΔShrout, ΔSo, LDP, NOA, PM adj, PROF, SUV, Total vol, AVAR

Table B.4: **Conditional Portfolio Sorts on Lagged Market Equity**

This table shows annual percentage returns of conditional double sorts of the most successful option characteristics (IV spread (ATM), IV spread (OTM), Skewness and AVAR) and 12-month lagged market equity. Stocks are first assigned to a low, medium and high category based on their idiosyncratic volatility and then sorted into 10 portfolios within each category based on the value of a given option characteristic in each month. All portfolios are equal weighted and rebalanced each month. The sample period is 1996-2018.

	Portfolio										
	1	2	3	4	5	6	7	8	9	10	99
Unconditional											
IV Spread (ATM)	19.52	16.71	12.72	12.24	11.25	9.62	9.36	7.45	6.01	-1.14	-20.49
IV Spread (OTM)	18.64	15.63	12.54	10.85	10.13	8.84	8.26	7.40	8.79	2.68	-15.77
AVAR	17.04	13.42	12.47	11.97	11.34	10.18	11.01	8.62	7.98	1.39	-15.39
Skewness	17.83	15.46	12.34	11.84	9.75	9.81	8.80	8.01	7.39	3.62	-13.99
Low Size Bin											
IV Spread (ATM)	19.18	14.74	39.91	19.19	7.05	2.35	15.17	1.53	2.19	-13.13	-33.50
IV Spread (OTM)	10.44	29.30	30.19	23.84	-2.71	5.92	-5.64	13.53	10.40	-10.05	-21.05
AVAR	18.16	7.62	6.11	31.72	11.77	19.62	9.49	8.85	-10.94	2.13	-16.01
Skewness	17.55	19.36	9.42	28.07	10.11	1.52	3.34	11.10	6.68	-5.38	-22.88
Medium Size Bin											
IV Spread (ATM)	19.77	16.43	16.75	14.70	12.81	11.07	7.53	9.98	3.58	-1.76	-21.52
IV Spread (OTM)	16.16	16.95	14.02	11.44	13.27	10.87	8.92	10.67	6.15	2.35	-13.81
AVAR	15.83	17.85	13.78	14.33	13.64	11.23	10.94	6.68	6.61	1.46	-14.37
Skewness	16.40	16.82	14.19	13.01	13.17	10.40	10.11	8.32	7.56	1.84	-14.56
High Size Bin											
IV Spread (ATM)	19.45	13.62	12.47	10.29	12.18	10.26	9.82	8.80	7.43	3.90	-15.54
IV Spread (OTM)	19.25	14.05	12.16	10.88	9.50	9.00	10.04	7.50	9.70	6.12	-13.13
AVAR	16.97	12.47	12.10	11.27	10.89	10.43	10.82	9.09	9.32	6.35	-10.63
Skewness	18.66	13.93	12.39	10.95	10.33	9.66	9.90	7.72	9.68	6.41	-12.24