Do Option Traders Boost Stock Anomalies?*

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Abstract

We investigate the relation between equity option returns and well-known stock return anomalies. For both the aggregate mispricing measure of Stambaugh, Yu, and Yuan (2015) and the special case of Bali, Cakici, and Whitelaw's (2011) MAX anomaly, we find evidence that option investors actively trade against mispricings in the underlying stocks. These results are in line with the literature on the higher sophistication of option traders and complement the notion of smart money in mitigating anomalies, but contrast previous analyses that argue for an additional mispricing in option returns. Finally, we find that buying put options is the main channel through which investors trade against the anomaly signals and document conclusive interactions between anomalies and arbitrage frictions.

Keywords: equity options, stock anomalies, informed trading, intermediary frictions
JEL Classification: G12, G13, G14

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1 Introduction

An extensive part of the finance literature is devoted to the explanation of the cross-section of returns. The seminal capital asset pricing model marks a milestone in this research area, but has been predominantly found to fail empirically (Black, Jensen, and Scholes, 1972; Frazzini and Pedersen, 2014). In response, additional factors have been proposed to address anomalous returns related to firm size, the book-to-market ratio, and momentum. Over the years, the literature has produced a whole "zoo" of factors with questionable significance (Cochrane, 2011; Harvey, Liu, and Zhu, 2016). At the same time, an equally large literature documents countless anomalies in the cross-section of returns that cannot be explained by standard risk factors. Recently, Hou, Xue, and Zhang (2018) have tried to replicate 447 of these anomalies and found evidence for widespread p-hacking. Nevertheless, far more than one hundred anomalies survive even under the most restrictive requirements for statistical and economic significance.

Compared to the large literature on stock mispricing, surprisingly little is known about whether and how such stock return anomalies propagate to prices and returns of equity options. With their asymmetric payoff profiles and high leverage, options are an ideal vehicle for sophisticated investors to trade in accordance with or against the signals provided by anomaly variables. On the one hand, options are by definition derivative instruments and therefore tightly linked to their underlying stocks, which would suggest that options just mechanically reflect the stock mispricing. On the other hand, the literature has documented salient frictions in stock and option markets that potentially lead to a certain degree of segmentation between these markets. For instance, Gârleanu, Pedersen, and Poteshman (2009) argue that option dealers are not able to perfectly hedge the option positions in their inventory, such that they charge a premium for the unhedgeable risk they face.[1] As a result, option prices and returns depend on the net demand of option end-users, contrasting the standard view of options being purely redundant derivatives. In particular, if investors trade on stock anomaly signals in the option market, their demand may result in anomalous option returns in excess of the effects induced by the mispricing of the underlying stock.

In principle, such a potential option-specific reaction to stock mispricing could go in either direction. That is, options could be even more mispriced as just implied by the mechanical link to the mispriced stock because option end-users follow the same misguided trading motives as the investors in the stock market. Alternatively, if the option traders actually recognize that a stock is mispriced, they may choose to trade *against* the mispricing. Consequently, the price impact of these arbitrage trades moves option prices closer to their hypothetical, true value in the absence of stock mispricing. Recent literature such as Boyer and Vorkink (2014) or Byun and Kim (2016) seems to point towards the first direction. But are stock anomalies indeed more pronounced within option markets? Or do option investors trade against the mispricing instead of *boosting* it? Which channels do they use to implement their goals and what are major impediments to their strategies? These are the central research questions of this paper.

As a first step towards an answer, we derive a model-free decomposition of stock excess returns into the return of an option-implied *synthetic forward* and the excess return of a *conversion trade*, that is, an offsetting portfolio of a long stock and a short synthetic forward. This decomposition may seem trivial, but we show that it allows a precise analysis of anomaly returns. Specifically, the returns of synthetic forwards capture the part of stock mispricing

[1] Further demand-dependent premia in option returns may result from funding constraints (Hitzemann et al., 2018) and stock illiquidity (Kanne, Korn, and Uhrig-Homburg, 2016), for example.

that is mechanically embedded in option prices, whereas the conversion returns quantify the additional response of the option traders to the anomaly signal.

We put these insights to the test in an analysis of U.S. stock and option returns. To quantify mispricing, we rely on the aggregate mispricing measure (MISP) proposed by Stambaugh, Yu, and Yuan (2015), which summarizes 11 prominent stock return anomalies. Guided by the model-free return decomposition, we analyze returns of MISP-sorted portfolios and find significant anomaly returns both in the stocks and synthetic forwards. However, the impact of mispricing on options is considerably smaller, which suggests that there is indeed a certain degree of segmentation between stock and option markets and that the option investors predominantly trade against the stock mispricing. In line with these results, we also find that call options written on overpriced stocks earn significantly lower raw returns, but this effect becomes insignificant after delta-hedging. Therefore, although call options written on an overpriced stock are mechanically overpriced, there is no evidence for an additional, option-specific reaction to the anomaly signal. On the other hand, for put options, raw returns are significantly higher and delta-hedged returns are significantly lower for more overpriced stocks. This finding suggests that sophisticated option traders preferably buy put positions to profit from inflated stock prices. We find corroborative results for the case of the MAX anomaly (Bali, Cakici, and Whitelaw, 2011), which contrasts the former literature that argues for an additional MAX-induced mispricing in option returns.

The anomaly-related price deviations between stock and option markets cannot be explained by exposures to common risk factors and variations in variance risk premia. In addition, we find that these deviations reasonably interact with arbitrage frictions as they are particularly large for illiquid stocks and stocks with high idiosyncratic volatility, in line with Stambaugh, Yu, and Yuan (2015). Intuitively, the higher these frictions are, the greater becomes the segmentation between stock and option markets, so that the option prices may detach more strongly from their mechanically implied values through informed option trading. Underpinning this view, we find that the documented price deviations are unlikely to represent exploitable arbitrage opportunities for outside investors, since transaction costs are comparatively large, in particular for highly mispriced stocks.

Related literature We contribute to the literature on the role of dumb and smart money in boosting or mitigating anomalies. Edelen, Ince, and Kadlec (2016) argue that institutional investors overall exacerbate stock return anomalies and Akbas et al. (2015) confirm this view for mutual funds, but find that hedge funds actively trade against mispricings in stocks. We complement the notion of smart money in mitigating anomalies, but focus on another type of potentially smart investors, the option traders, and analyze their impact on returns of equity options.

For the special case of Bali, Cakici, and Whitelaw's (2011) MAX anomaly, Boyer and Vorkink (2014) and Byun and Kim (2016) document anomalously low call option returns, which they attribute to an additional mispricing in options with lottery-like payoffs. We find corroborative results for this mispricing in raw option returns, but show that the patterns in delta-hedged option returns rather suggest that option investors even trade *against* this anomaly. Related, Hayunga et al. (2012) document a positive relation between stock mispricing and price disequilibria between stock and option markets in a short sample around the short-sale ban of 2008, but the quantitative impact of these price divergences on stock and option returns remains unclear.

Other notable studies devoted to the reaction of options to stock mispricing are Battalio and Schultz (2006) and Choy and Wei (2018), which focus on options written on Internet stocks during the dot-com bubble and stocks subject to attention-induced buying pressure, respectively. Neither of these two studies, however, offers a simultaneous analysis of the purely mechanical and the options-specific pricing response to the anomaly signals. Finally, Cao et al. (2017) document predictability of hedged option returns by a variety of anomaly-related stock characteristics, but do not analyze the effects in raw option returns. In addition, there is virtual no predictability in stock returns within their sample, which prevents further insights into the impact of stock mispricing on option returns.

Through the distinction between the mechanical and option-specific channel that could lead to option mispricing, we also contribute to the literature about the different investor sophistication in the option and stock market. Easley, O'Hara, and Srinivas (1998) show that informed traders may prefer to trade in options because of their high leverage and better liquidity and find that option trading volume predicts future stock prices. An extensive literature is confirming this view.[2] On the other hand, An et al. (2014) point out that sophisticated investors may trade in either the stock or option market and document a two-sided return predictability between stock and option markets. Muravyev, Pearson, and Broussard (2013) challenge all these studies, as they find that option price changes track stock price changes in the presence of looming arbitrage opportunities, which calls the superiority of the option-implied information into question. We reconcile these contradictory views, since we find evidence for the higher sophistication of option traders, but the resulting difference between actual and option-implied synthetic stock prices does not result in arbitrage opportunities.

From a conceptual point of view, our study also contributes to the literature that analyzes

[2]See Chakravarty, Gulen, and Mayhew (2004); Ofek, Richardson, and Whitelaw (2004); Cremers and Weinbaum (2010); Roll, Schwartz, and Subrahmanyam (2010); Xing, Zhang, and Zhao (2010); Johnson and So (2012); Mohrschladt and Schneider (2018), for example.

market integration through structural links between derivatives and underlying assets. For instance, Kapadia and Pu (2012) document anomalous pricing discrepancies between equity and credit markets as a result of limits of arbitrage. Choi and Kim (2018) analyze the joint predictability of equity and bond returns and find large differences between estimated risk premia in the two markets. These studies interpret stocks and bonds as derivatives on the firm value to motivate their analyses. By contrast, we focus on options written on mispriced stocks, which allows us to analyze the propagation of directly measurable stock return anomalies to option returns.

The remainder of this paper is structured as follows. In Section 2, we derive a model-free decomposition of anomalous stock returns. Section 3 describes our data sample, the mispricing measure, and the empirical methodology. In Section 4, we analyze returns of stocks and option portfolios in dependence of aggregate mispricing, whereas Section 5 covers the MAX anomaly. The interactions between mispricing and arbitrage frictions are discussed in Section 6. Section 7 concludes the paper.

2 Mispriced Stocks and the Option Market

Prominent asset pricing studies in the option market (Goyal and Saretto, 2009; Cao and Han, 2013, for example) usually focus on delta-hedged returns of single options or straddle portfolios, with the goal to identify premia in option returns beyond the effects induced by the underlying stock. Likewise, we are interested in additional, option-specific effects in the presence of stock mispricing. Since stock mispricing may or may not translate to option mispricing purely mechanical, such an analysis is only meaningful when it is accompanied by a comparison with the direct price implications for options written on mispriced stocks.

To this end, we derive a model-free decomposition of stock returns, which enables us to disentangle these two channels.

Specifically, consider a non-dividend paying stock with price S_t, and let C_t and P_t be prices of call and put options, respectively, written on this stock with common maturity date T and strike price X. In general, we can decompose the excess return of the stock into returns of two option portfolios:

$$\begin{aligned} r_S^e &= \frac{S_T - S_0}{S_0} - r(0,T) \\ &= \frac{F_T - F_0 + (S_T - F_T) - (S_0 - F_0)}{S_0} - r(0,T) \\ &= \frac{F_T - F_0}{S_0} + \left(\frac{G_T - G_0}{S_0} - r(0,T)\right) \\ &= \hat{r}_F + \hat{r}_G^e. \end{aligned} \tag{1}$$

where $r(t_1, t_2) = \exp\Big(\int_{t_1}^{t_2} r(u)\, du\Big) - 1$ denotes the risk-free interest earned between t_1 and t_2, with $r(t)$ being the short rate, $F_t = C_t - P_t$ is the price of a synthetic forward, and $G_t = S_t - C_t + P_t$ corresponds to a so-called conversion trade, i.e., a long position in the stock combined with a short synthetic forward. In words, the stock excess returns can be generically decomposed in the return of a synthetic forward and the excess return of a conversion trade, where both returns are defined relative to the stock price S_0. These returns, $\hat{r}_F$ and $\hat{r}_G^e$, are closely related to the leverage-adjusted option returns considered later on, where we scale option portfolio gains by their stock exposure.

To capture the option-implied value of the given stock, we follow Ofek, Richardson, and Whitelaw (2004) and define the synthetic stock price as

$$S_t^* := C_t - P_t + e^{-\int_t^T r(u) du} X. \tag{2}$$

The option payout is naturally defined in terms of the observed stock price, so that $S_T^* = S_T$. If there are no frictions and differences of opinion, the standard put-call parity implies that this equality also holds before option maturity: $S_t^* \equiv S_t$. In practice, however, there may be deviations between these two prices, for example as a result of demand-dependent premia for unhedgeable risk (cf. Gârleanu, Pedersen, and Poteshman, 2009).

For the special case of at-the-money-forward options, i.e., with $X = S_0(1 + r(0,T))$, the return decomposition given in Eq. (1) uncovers such potential deviations between actual and synthetic stock prices:

$$
\begin{aligned}
r_S^e &= \hat{r}_F && + \hat{r}_G^e \\
&= \frac{(S_T^* - X) - (S_0^* - e^{-\int_0^T r(u)du} X)}{S_0} && + \frac{X - (S_0 - S_0^* + e^{-\int_0^T r(u)du} X)}{S_0} - r(0,T) \\
&= \frac{S_T^* - S_0^*}{S_0} - r(0,T) && + \frac{S_0^* - S_0}{S_0}.
\end{aligned}
\tag{3}
$$

That is, the return of a synthetic forward formed from at-the-money-forward options precisely captures the stock excess return as expected by the option traders. On the other hand, the excess return of the conversion trade quantifies the different valuations of stock and option traders for the stock.

These results hold without any assumption about the valuation of the given stock, but provide additional insights in the light of stock mispricing. To fix ideas, suppose in the following that the given stock is *overpriced* (the results for underpriced stocks are analogous, only in the opposite direction). That is, the stock price S_0 is higher than its (unobservable) fundamental value V_0 and, equivalently, the stock return r_S is lower than the corresponding fair, risk-adequate return r_V.[3]

If options were just purely redundant derivatives, such that $S_t^* \equiv S_t$, the conversion excess return $\hat{r}_G^e$ would be zero and the synthetic forward would earn the same anomalously low return as the stock,

$$\hat{r}_F = r_S^e < r_V^e. \tag{4}$$

Alternatively, the signal provoking the stock overpricing could also result in a non-zero option net demand and, in the presence of frictions, lead to a corresponding price impact on options and the synthetic stock price.

Therefore, there are two additional cases to consider. On the one hand, option end-users could trade in the direction of the anomaly signal, i.e., *boost* the anomaly by buying call options, selling put options, or both. Consequently, the synthetic stock price would be even more overpriced than the actual stock, and the synthetic forward would perform even worse than the stock:

$$\hat{r}_F < r_S^e < r_V^e. \tag{5}$$

In this case, the conversion trade would yield a positive excess return $\hat{r}_G^e = r_S^e - \hat{r}_F > 0$.

On the other hand, option traders could sell call options or buy put options to actively trade *against* the stock anomaly, such that

$$r_S^e < \hat{r}_F. \tag{6}$$

As a result of the corrective influence of the option traders, the synthetic stock would actually be less overpriced – or even correctly priced – such that the forward return exceeds the stock excess return.

[3]For simplicity, we assume that the overpricing results in *pathwise* underperformance of the stock. This assumption could be easily relaxed by considering expected, instead of realized returns in the remainder of this section.

To sum up, forward returns indicate whether and to what extent the overpricing of the stock is reflected in the option prices. In addition, conversion trades quantify the option-specific response to the stock anomaly resulting from option trading in line with or against the anomaly.

These results also have intuitive implications for returns of individual options. By the very definition, naked options are levered positions in the option-implied synthetic stock. Therefore, if the option market does not fully offset the stock overpricing, raw call returns are also comparatively low and put returns are high. Furthermore, a delta-hedged option can be interpreted as a levered position in a long-short portfolio of the synthetic and actual stock, i.e., a short conversion trade. Therefore, delta-hedged option returns capture the impact of the anomaly signal on option returns beyond the effect mechanically induced by the stock mispricing, in line with the usual demand-based interpretation of delta-hedged option returns. Consequently, if a call option is less (more) overpriced than implied by the stock mispricing, the delta-hedged excess return will be positive (negative), and vice versa for put options.

Note that this final line of thought is not completely rigorous because the time-varying nature of the option-embedded leverage and the dependence between the return denominator and stock mispricing may counteract the hypothesized effects in the returns of individual options. To alleviate these concerns, we present in Appendix A a simple model featuring options written on an overpriced stock and find that the model-implied option returns behave in line with our intuition.

3 Data and Methodology

Our main data source is OptionMetrics' IvyDB, which contains end-of-day bid and ask quotes of all U.S. equity options and the underlying stocks, trading volumes and open interest, as well as implied volatilities and option greeks. We consider only options written on common stocks with standard settlement and expiration dates (i.e., the Friday before the third Saturday in a month or the third Friday in a month after February 1, 2015). Following the literature (e.g., Goyal and Saretto, 2009), we only keep option observations with a positive implied volatility, a positive bid price, and a bid-ask spread larger than the minimum tick size.[4] At the initial portfolio formation date, we apply some further filter criteria, following Frazzini and Pedersen (2012). We focus on stocks with a price between \$5 and \$1 000. In addition, we keep only options with positive open interest and a bid-ask midpoint price within standard arbitrage bounds. We also drop stock-months with dividend payments and options with a time value below 5% of the options' price to control for the early exercise possibility.[5] Then, for each stock in our sample, we select the pair of call and put options expiring in the next month whose strike price is closest to the forward price of the stock, as long as the distance between strike and forward price is at most 10% of the stock price.[6] The final sample consists of 317 269 observations between January 1996 and December 2017, with an average cross section of 1 211 stocks per month.

[4]The minimum tick size for options written on stocks in the penny pilot program is \$0.01 (\$0.05) if the option price is below (above) \$3. For all other options, the minimum tick size is 0.05 (\$0.10).

[5]We define the time value of an option as the difference between its midpoint price and the intrinsic value, i.e., the payoff earned from an immediate exercise of the option.

[6]Analyses of standard at-the-money options as considered by Goyal and Saretto (2009), for example, yield similar results as the ones reported in the following.

Return calculation Following the literature (e.g., Goyal and Saretto, 2009), we consider returns from the first trading day immediately following an expiration date until the next expiration date. To form portfolios, we match the observations at the portfolio formation date with monthly explanatory variables from the end of the preceding month.[7] For a given option O, we define the raw option gain as

$$\pi_O(t_0, t_N) = O_{t_N} - (1 + r(t_0, t_N))O_{t_0}, \tag{7}$$

where O_t is the option's time-t price and $r(t_0, t_N)$ is the risk-free interest earned between the date t_0 of portfolio formation and the expiration date t_N. The terminal value of the option, O_{t_N}, is set to its payoff at maturity. Finally, we define raw and leverage-adjusted returns as

$$\begin{aligned} r_O &= \frac{\pi_O(t_0, t_N)}{O_{t_0}}, \\ \hat{r}_O &= \frac{\pi_O(t_0, t_N)}{\left|\Delta_{t_0}\right| S_{t_0}}, \end{aligned} \tag{8}$$

where Δ_t and S_t are the option's delta and the price of the underlying stock in t, respectively. Analogously, we define delta-hedged returns without (r_{dh}) and with ($\hat{r}_{dh}$) leverage adjustment by replacing the raw option gain π_O in Eq. (8) with the corresponding delta-hedged gain as defined by Bakshi and Kapadia (2003) and Cao and Han (2013):

$$\pi_{dh}(t_0, t_N) = O_{t_N} - O_{t_0} - \sum_{n=0}^{N-1} \Delta_{t_n}(S_{t_{n+1}} - S_{t_n}) - \sum_{n=0}^{N-1} r(t_n, t_{n+1})(O_{t_n} - \Delta_{t_n} S_{t_n}). \tag{9}$$

[7] Other specifications, such as holding options from the end of a month until the expiration date in the month after next, yield qualitatively similar results.

Identifying mispriced stocks As response to the myriads of cross-sectional stock return anomalies documented in the literature, recent studies rather focus on aggregate mispricing measures that diversify away the noise in the individual anomaly variables.[8] Specifically, in our analysis, we rely on the MISP measure of Stambaugh, Yu, and Yuan (2015), defined as the average percentile rank from separate portfolio sorts on 11 prominent return anomalies.[9] The included anomalies are well-known for long period of times, but result still in anomalous returns.[10] Furthermore, in Section 5, we analyze the specific response of option markets to the MAX anomaly, recently documented by Bali, Cakici, and Whitelaw (2011).

Descriptive statistics Table 1 shows some descriptive statistics on our sample of stocks and options. For each of the considered variables, we report the full-sample mean, standard deviation, and the 5%, 50%, and 95% quantile. The first line shows results for MISP, our main measure of stock mispricing. Given that MISP is defined as an average percentile rank, the mean and median in our sample are indeed fairly close to 50%. On the other hand, the 5% and 95% quantiles are 28.77 and 72.46 in our sample, respectively. This finding highlights that our sample does not contain the most extreme deciles analyzed in Stambaugh, Yu, and Yuan (2015), presumably since there are no liquid options written on the corresponding stocks. Similarly, the 95% quantile of MAX, i.e., the highest daily return within a month, is 14.77%, which is substantially lower than the 23.6% average MAX for the highest MAX decile portfolio reported by Bali, Cakici, and Whitelaw (2011). By implication, our results are not driven by the most extremely mispriced stocks in the market.

[8] Some notable examples are Lewellen (2015), Stambaugh, Yu, and Yuan (2015), Green, Hand, and Zhang (2017), Light, Maslov, and Rytchkov (2017), Stambaugh and Yuan (2017), and Engelberg, Mclean, and Pontiff (2018).

[9] The MISP measure may be obtained at `http://finance.wharton.upenn.edu/~stambaug/`.

[10] A potential driver of this persistence may be biased analyst recommendations (cf. Guo, Li, and Wei, 2018).

The remainder of Table 1 shows further summary statistics on stock and option characteristics, as well as average returns of conversion trades and synthetic forwards. In particular, we find a substantial variation in the embedded leverage, i.e., the product of the options' absolute delta, $|\Delta|$, and the stock price S relative to the option price O, despite our restriction on at-the-money-forward options. Because of this variation in leverage, it matters whether we scale delta-hedged gains with the option price O or with the stock exposure $|\Delta|\, S$. For this reason, we consider both types of option returns in the following.

4 Empirical Analysis of Stock and Option Mispricing

4.1 Portfolio sorts

To analyze mispricing effects in returns of stocks and options, we form monthly-rebalanced decile portfolios by sorting on the stock-specific MISP measure. The first column of Table 2 shows the resulting Fama and French (1993) alphas of the corresponding stock returns. In line with Stambaugh, Yu, and Yuan (2015), we find decreasing alphas in the portfolio rank, indicating that stocks with high MISP are indeed overpriced.

In the next column, we report the alphas of synthetic forwards constructed from the chosen at-the-money-forward call and put options with one month to maturity and find a highly significant long-short alpha of -1.34% per month. Thus, the stock mispricing is also present in the option prices. On the other hand, we also find a negative long-short alpha of -0.11% per month for conversion returns. That is, the option prices reflect roughly $0.11/1.34 = 8\%$ less mispricing than the underlying stocks, in line with the view that option investors actively trade *against* the stock mispricing.

It stands out that all conversion trade returns are significantly negative, which indicates that synthetic stocks are on average cheaper than the actual stocks. This effect could result from structural differences between actual and synthetic stock positions unrelated to stock overpricing. In particular, if stocks provide additional benefits that are not provided by synthetic stock positions, like voting rights (cf. Kalay, Karakaş, and Pant, 2014), synthetic stock prices might be lower than the actual ones.[11] Such effects tend to decrease conversion returns and inflate the returns of synthetic forwards. In this case, synthetic forwards do not exactly capture the option-implied valuation of the actual stock, but rather of a hypothetical stock without these stock-specific benefits. Consequently, to measure the pure mispricing effect, we would have to subtract the premium caused by these benefits from the conversion returns and add it to the synthetic forward instead. For a simple ad-hoc analysis along these lines, we report in the last two columns of Table 2 results for adjusted returns, where we approximate the MISP-unrelated effect by the monthly mean conversion return. Under this specification, adjusted conversion returns scatter around zero per construction and show a clear pattern along the stock-specific MISP measure: positive anomalous returns for underpriced stocks and negative returns for overpriced stocks. As a result, with this adjustment, also the synthetic forward returns are lower in absolute values, i.e., less undervalued for the low-MISP portfolios and less overvalued for the high-MISP portfolios.

[11] Another potential driver for lower synthetic stock prices may be short-sale constraints in the stock market (Lamont and Thaler, 2003; Ofek, Richardson, and Whitelaw, 2004). This channel is obviously related to potential differences in overpricing in stock and option markets, but there also may be an impact of short-sale constraints independent from the overpricing captured by the MISP measure.

Value weighted portfolios In the above analysis, we form equally weighted portfolios of stocks, synthetic forwards, and conversions. The choice of equal weights is in line with most of the empirical studies on option returns (see Goyal and Saretto, 2009; Cao and Han, 2013; An et al., 2014, for example). But to rule out concerns about the overstatement of outliers, we show in Table 3 results from a portfolio sort on MISP using value weighting. Specifically, we consider both the standard stock-value weights, i.e., the market capitalization of the firms, as well as the value of open interest, defined as the product of the option mid price and the open interest. We calculate this measure for the chosen at-the-money-forward call and put options separately and average them afterwards. Throughout, we find similar patterns in the reported Fama and French (1993) alphas than for the case of equal weighting.

Risk adjustments Premia on anomaly variables are only anomalous if they cannot be explained by compensation for systematic risk. In Table 2, we focus on the Fama and French (1993) three-factor model, arguably still the benchmark model for the cross-section of stock returns, but it may be inappropriate to capture the MISP premia in stocks and options. In particular, synthetic forwards and conversion trades may be subject to other types of risks not reflected in the size and value factor. To rule out these possibilities, we consider alternative factor models in the following.

Our first choice is the factor model proposed by Fama and French (2018), consisting of the standard Fama and French (1993) factors, the profitability and investment factors of Fama and French (2015) and Carhart's (1997) momentum factor. As shown in Table 4, the resulting patterns in alphas of forwards and conversions are very similar to the case of the Fama and French (1993) three-factor model and the corresponding long-short alphas are highly significant as well.

Higher order risks are a likely alternative explanation for additional premia in option returns. Nevertheless, we also find significant alphas with respect to the factor model of Cremers, Halling, and Weinbaum (2014), which includes the market return and two factors to capture aggregate jump and volatility risk. Finally, we consider the 12-factor model of Vasquez (2017), which consists of the standard size, value, and momentum factors, as well as higher-order moments of the stock and option market return. Even this extensive factor model cannot explain the MISP effect in conversion returns, whereas the alpha of long-short forward returns is no longer significant. In this sense, the relative mispricing of stocks with respect to their options is more robust than the mispricing of options relative to the fundamental value. This result is not overly surprising given the special characteristics of conversion trades. By construction, conversion trades correspond to a static portfolio with deterministic payoff, so that returns are unlikely to be driven by future factor realizations. On the other hand, the variation in synthetic forward and conversion returns could be driven by option-specific frictions, which is why we take a closer look at the cross-section of the test portfolios in the following.

Portfolio characteristics In Table 5, we report further characteristics of the MISP-sorted portfolios to identify potential alternative explanations for the observed effects in returns. By construction, MISP is increasing in the portfolio rank, but so does idiosyncratic volatility, as defined by Ang et al. (2006), and several measures of stock illiquidity. In addition, both the market cap of the firm and the dollar amount invested in the considered at-the-money-forward options are lower for high-MISP stocks. In the last row, we consider the variance risk premium as defined by Carr and Wu (2009) and also find a strong negative trend along the MISP dimension.

We analyze the impact of these variables on our decomposed anomaly returns in a regression setup in Section 4.2. In addition, the variation in idiosyncratic volatility and illiquidity points to a possible interaction between such arbitrage frictions and the mispricing in stock and option markets, which we further discuss in Section 6.1.

Variance risk The pronounced heterogeneity in the variance risk premium across the MISP portfolios could provide a risk-based explanation of the patterns in synthetic forwards and conversion trades. As discussed by Bakshi and Kapadia (2003), option returns compensate for variance risk with a premium that is proportional to the option vega. According to standard theory, however, conversion trades have zero vega and therefore no exposure to variance risk. But in reality, in a world with frictions, variance risk may still have an impact on conversion returns. To investigate this hypothesis, we first form monthly-rebalanced decile portfolios on the variance risk premium. Within each of these portfolios, we form ten conditional MISP-portfolios, which we then aggregate across the variance risk portfolio rank. Table 6 shows that the resulting portfolios have almost no variation in the variance risk premium, but MISP is still strongly increasing. For these test portfolios, we find again significantly negative long-short alphas for stocks, forwards, and conversions, in line with our main analysis.

4.2 Regression analysis

To conclude the analysis of the components of anomaly returns, we show in Table 7 the results from Fama-MacBeth regressions of synthetic forward and conversion trade returns.

First of all, we find a significantly negative impact of MISP on monthly forward and conversion returns of -24.14 and -2.88 basis points per standard deviation increase, respectively. These coefficients are quite low in comparison with the long-short returns documented in Table 2, but this is expected, since anomalies are usually more pronounced in the tails. Specifically, the MISP difference between the lowest and highest MISP portfolio amounts to about four standard deviations, and indeed, the estimated regression coefficients are about a quarter of the long-short returns. As shown in specifications (2) and (4), these results are robust to the inclusion of control variables. Specifically, we control for idiosyncratic volatility, Amihud (2002) stock illiquidity, the relative option bid-ask spread (averaged over the at-the-money-forward call and put option), firm size, the dollar value of open interest (also averaged over the call and put option), and the fraction of call open interest relative to put open interest as a summary measure of end-user demand in call and put options. Finally, we control for the stock-specific variance risk premium and find a significantly positive effect in conversion returns, which is surprising since conversions should have no exposure to variance risk by construction. In any case, this effect does not interfere with the mispricing effect in conversion returns, confirming our previous results on VRP-controlled portfolio sorts (see Table 6).

Finally, in a frictionless market, conversion excess returns should be zero, so that frictions should amplify *any* existing deviation – positive or negative – between actual and synthetic stock prices. To investigate this idea, we multiply all variables that are related to arbitrage impediments with the sign of the conversion return to capture the impact of the respective variable on the absolute magnitude of mispricing. In the corresponding regression model (5), we find indeed that idiosyncratic volatility as well as stock and option illiquidity increase the absolute conversion returns, and so does a smaller firm size. We also find a positive effect of the absolute value of dollar open open interest, which could potentially result from a higher end-user demand pressure.

4.3 Separate effects in call and put options

If there are sophisticated option traders present in the market who are informed about the stock overpricing, as suggested by the results in Table 2, they may choose to either sell call options, buy put options, or both. The resulting demand pressure translates to premia in expected option returns if option dealers are unable to hedge perfectly (cf. Gârleanu, Pedersen, and Poteshman, 2009), which in turn result in the negative conversion trade returns present in the data. In Table 8, we separately analyze returns of call and put options to uncover such premia. For both option types, we report Fama and French (1993) alphas of raw and delta-hedged returns, each relative to the option price and relative to the product of absolute option delta and the stock price.

First of all, raw option returns exhibit patterns in line with the pure mechanical effect induced by the overpricing of the underlying stocks: Call returns are decreasing in MISP and put returns are increasing, irrespective of the chosen return denominator, with highly significant long-short alphas. With delta-hedging, call returns are throughout insignificant and exhibit no pattern along the MISP dimension. This finding suggests that call options are about as overpriced as mechanically implied by the stock overpricing. In particular, there is no evidence for an *additional* MISP-driven overpricing in call option returns. On the other hand, we find a pronounced negative relation between stock overpricing and delta-hedged put option returns, with significantly negative long-short alphas of -1.57% and -0.43% without and with leverage adjustment, respectively. Therefore, put options reflect even less mispricing than the underlying stock, which suggests that put options are the main channel through which sophisticated option traders express their information about stock overpricing. This finding is intuitive, since buying put options requires less margin capital than selling call options and is therefore preferred by funding-constrained option end-users.[12]

5 The MAX Anomaly in Option Returns

The analysis discussed in Section 4 is based on the 11 prominent stock anomalies selected by Stambaugh, Yu, and Yuan (2015). Recently, Bali, Cakici, and Whitelaw (2011) have documented that stocks with an extreme maximum daily return in the previous month are overpriced, which suggests that investors prefer such lottery-like stocks. Importantly, Byun and Kim (2016) find that call options written on such stocks strongly underperform comparable options on non-lottery stocks. Related, Boyer and Vorkink (2014) find a negative effect of option-individual total skewness on expected option returns to maturity. Contrasting our results that option traders are informed about mispricing, both studies argue that there exists an additional lottery-driven anomaly in options beyond the mechanically induced effect of the underlying stocks' anomalous returns. But it stands out that neither of these studies consider hedged returns to verify this claim,[13] which motivates the following analysis of the MAX effect in stocks, synthetic forwards and conversion trades.

Specifically, Table 9 shows results from a portfolio sort on MAX (i.e., the highest daily return in the previous month).[14] Similar to the case of the MISP effect (see Table 2), we find a

[12] Santa-Clara and Saretto (2009) argue that margin requirements and the associated margin calls have an important impact on the profitability of strategies involving writing put positions, but a similar argument applies to short call positions.

[13] Byun and Kim (2016) also document violations of the put-call parity to support a separate MAX effect in call option returns. According to the model presented in Appendix A, however, the put-call parity needs not to hold for mispriced stocks even when there is no additional mispricing in the option market.

[14] Alternative proxies like the second-highest return, an average over the highest n returns, or measures of idiosyncratic volatility give similar results, see Table A3 in Appendix B. The specific patterns in forwards an conversion with regard to the MAX effect are also robust to controlling for other risk factors, as shown in Table A2.

significantly negative long-short Fama and French (1993) stock return alpha of -1.28% per month, which can be decomposed in negative returns of synthetic forwards and conversion trades. The average long-short return of synthetic forwards generates only about 90% of the average MAX effect in stock returns, which indicates that the option market is slightly less prone to MAX-induced overpricing than to the anomalies summarized in the MISP measure.[15] Finally, the significantly negative long-short alpha in conversion trades indicates that the synthetic stock price is significantly lower than the actual stock price, contrasting the additional MAX-induced overpricing of call options proposed by Byun and Kim (2016).

To make the latter argument more explicit, we also consider call and put option returns in Table 10. The first two columns show a clear negative pattern along the MAX dimension for both standard and leverage-adjusted call option returns. This finding is completely in line with Byun and Kim (2016). In addition, we document a strong positive trend in put options. These two effects could either result from the mechanical link to the underlying stock return or from an excess long (short) demand in call (put) options because of their lottery-like characteristics. But in the latter case, the effect should also be present in delta-hedged option returns. Table 10 clearly shows that this is not the case. All delta-hedged returns are either insignificant or significant with a different sign than the raw option returns. Such a change of sign contradicts an additional, option-specific overpricing, but is perfectly in line with the notion of better informed option traders. In summary, the analysis of the MAX anomaly confirms the result for the MISP anomaly that options written on mispriced stocks may be mispriced as well, but to a lesser degree as mechanically induced by the stock mispricing.

[15] Lin and Liu (2018) find that the MAX effect in the stock market is driven by the demand of individual retail investors. Such individuals are unlikely to play an important role in the option market, such that the aggregate information on the MAX anomaly embedded in stock and option prices may be much more different than in the case of the MISP anomaly.

6 Arbitrage Frictions

The persistence of anomalies in prices and returns is puzzling at first sight, but could well be explained with specific risks and frictions that deter arbitrage trades. In Section 6.1, we discuss the relation between such arbitrage frictions and mispricing in stock and option markets. Closely related, in Section 6.2, we show that potential arbitrage strategies implied by the results presented in Section 4 are not feasible in practice because of high trading costs.

6.1 Mispricing and arbitrage frictions

Mispricing can only occur in equilibrium if there are substantial frictions that impede arbitrage mechanisms. Shleifer and Vishny (1997) point out that arbitrageurs care about idiosyncratic volatility since they are likely to hold not perfectly diversified portfolios. Related, Stambaugh, Yu, and Yuan (2015) document that a long-short portfolio of overpriced and underpriced stocks, as indicated by their MISP measure, realizes lower returns with increasing idiosyncratic volatility, i.e., higher arbitrage risk. That is, the *potential* overpricing in a high-MISP stock only results in low returns when arbitrageurs are reluctant to trade against it. If we extend this mindset to include the option market, there emerge two additional channels through which arbitrage impediments influence the pricing effects of anomaly signals. First, only if there are specific risks and frictions that deter arbitrage trades *between* the stock and option markets, then these markets can be segmented, so that market-specific trading behavior may lead to deviations between stock prices and their option-implied counterparts, as captured by conversion trades. Second, even if direct arbitrage trades between the stock and option market were infeasible, mispriced options would still represent lucrative investment opportunities with the outlook for high excess returns. As a result, the mispricing in options captured by synthetic forwards can only persist when there are also frictions *within* the option market, impeding the profitability of long-short option strategies. In the following, we analyze these channels for two different dimensions of arbitrage frictions: Idiosyncratic volatility as a measure of arbitrage risk and stock illiquidity, which constitutes an important friction faced by arbitrageurs.

We form monthly quintile portfolios on idiosyncratic volatility, and within each of these portfolios, we form five portfolios on MISP. Table 11 shows Fama and French (1993) alphas of the resulting 25 portfolios. Panel A corresponds to the forward returns, Panel B contains results for conversions. For both components of stock returns, we find in each idiosyncratic volatility portfolio significantly negative MISP long-short alphas. Importantly, these alphas are overall decreasing in idiosyncratic volatility. Arbitrage risk therefore results in a more pronounced overpricing in both synthetic forwards and conversion trades. By implication, their sum, i.e., the mispricing in excess stock return is also stronger for higher levels of idiosyncratic volatility, in line with Stambaugh, Yu, and Yuan (2015).

Table 12 shows analogous results for double-sorted portfolios on Amihud (2002) stock illiquidity and MISP. Consistent with our intuition, we find signifcantly negative MISP long-short conversion alphas that are larger in magnitude for higher levels of illiquidity. On the other hand, long-short forward returns are also significantly negative, but they exhibit no systematic variation across the liquidity portfolios. For the most illiquid stocks, however, synthetic forwards even show no more signs of MISP-induced overpricing, whereas the respective conversion trade return peaks at -0.17%. A potential explanation for this finding could be that higher stock illiquidity mainly acts as arbitrage friction between stock and option markets without direct implications for the option market itself, so that synthetic and actual stock prices can deviate more drastically.

To conclude this analysis of the interaction between arbitrage frictions and mispricing, we show in Table 13 the results from Fama-MacBeth regressions of forward and conversion returns on MISP, idiosyncratic volatility, stock illiquidity, and their interactions. We standardize these variables such that they have a full-sample mean of zero and unit standard deviation. As a result, the estimated coefficients of MISP, idiosyncratic volatility, and stock illiquidity quantify the marginal effect of the respective variables given that the others are equal to their respective mean.

The regression results are overall in line with the previous findings from the double-sorted portfolios. In the case of synthetic forwards, a higher idiosyncratic volatility leads to a larger mispricing premia, whereas stock illiquidity has no effect. For conversion trades, on the other hand, both two-way interactions and also the three-way interaction between mispricing, idiosyncratic volatility, and mispricing are highly significant. Therefore, the negative impact of MISP on conversion returns is particularly strong for more pronounced arbitrage frictions.

6.2 Trading against stock mispricing

Given the highly significant negative long-short returns for conversion trades, it is a natural question to ask whether this finding gives rise to a profitable arbitrage strategy. As we show in the following, this is not the case, since transaction costs of conversion trades are comparatively large.

To earn the premium resulting from the overpricing of stocks relative to the associated options, one could combine a short stock position with a long position in a synthetic stock, forming a *reverse conversion trade.* With transaction costs, this strategy generates the following excess return:

$$r_{rev} = \frac{H_T - H_0(1+r)}{H_0}, \tag{10}$$

$$H_0 = C_0^{\text{ask}} - P_0^{\text{bid}} - S_0^{\text{bid}}, \tag{11}$$

$$H_T = -K, \tag{12}$$

where C_0^{ask}, P_0^{bid}, and S_0^{bid} are the respective bid or ask prices of the at-the-money-forward call and put option and the stock and K is the strike price of the options. Note that $H_0 < 0$, so that this strategy corresponds to a risk-free loan.[16]

Importantly, our data set only contains quoted spreads, which are likely to be substantially larger than the effective spreads relevant for the arbitrage-seeking investor. In particular, Mayhew (2002) and De Fontnouvelle, Fishe, and Harris (2003) show that the ratio between effective and quoted spreads is for equity options less than 50%. Therefore, we follow Cao et al. (2017) and assume that the effective spreads are a fixed fraction δ of the quoted spread.

In Table 14, we report average reverse conversion returns of MISP-sorted portfolios with transaction costs. The first column shows results for $\delta = 0\%$, which corresponds to the case of zero transaction costs as in our main analysis, leading to an average long-short return of 0.10% per month.[17] The remaining columns show analogous results for different values of δ. Whereas there is still a small arbitrage profit for $\delta = 10\%$, a proportion of 15% is roughly the break-even point. For higher, probably more realistic levels of effective spreads, the long-short

[16] In this analysis, we abstract from stock borrowing costs, which are known to diminish the returns to short selling (Muravyev, Pearson, and Pollet, 2018). In particular, such borrowing costs render many of the seeming arbitrage opportunities based on stock overpricing unprofitable (see also Hu, 2018).

[17] The minor deviations between Table 14 and Table 2 result from the different scaling of the portfolio gains. In our main analysis, we focus on the separation of anomaly returns and scale portfolio gains therefore with the stock price, whereas the returns considered here are defined relative to the actual capital invested in the strategy.

returns are significantly negative. Thus, although we find evidence for overpricing of stocks relative to the option-implied stock value, this difference can hardly be exploited by a simple arbitrage strategy.

Nevertheless, there are options in the sample where the arbitrage strategy would be profitable even under the quoted spreads. Such an arbitrage strategy exists only if the actual bid-ask interval of the stock is disjoint from the bid-ask interval of the synthetic stock position. Since we excluded stock-months with dividend payments from our sample, we define synthetic ask and bid quotes of a given stock as[18]

$$\widetilde{S}_t^{\text{ask}} = C_t^{\text{ask}} - P_t^{\text{bid}} + PV(K), \tag{13}$$

$$\widetilde{S}_t^{\text{bid}} = C_t^{\text{bid}} - P_t^{\text{ask}} + PV(K), \tag{14}$$

where $PV(K)$ is the discounted strike price.

As a first result, we find that in over 85% of observations in the full sample, the actual stock bid-ask interval is enclosed by the synthetic one. By this means, traders in the synthetic stocks face inferior prices in comparison with the actual stock prices, confirming the results from Hu (2018). Furthermore, in over 97% of the cases, the bid-ask intervals are overlapping, such that there is no arbitrage opportunity present according to the quoted spreads. On the other hand, there are *some* arbitrage opportunities, even when evaluated with quoted spreads. In Fig. 1, we provide a more detailed insight into the distribution of arbitrage opportunities within the MISP-sorted portfolios.

For the lowest- and highest-MISP portfolios, the share of arbitrage opportunities is the largest with over 3.5% of the observations. But whereas for low MISP values both types of arbitrage

[18] Since we exclude dividends and focus on options with not too low time value, we do not incorporate the possibility for early exercise here. See Battalio and Schultz (2006) and Muravyev, Pearson, and Broussard (2013) for alternative definitions that incorporate the early exercise premium.

opportunities – stock underpricing or overpricing relative to the synthetic stock – occur with almost equal proportion, the seeming arbitrage opportunities in high-MISP stocks mostly arise from relative overpricing of the stock, in line with our previous analyses.

7 Conclusion

In this paper, we analyze the specific response of option markets to stock mispricing. Since there are frictions in and between stock and option markets, option prices may contain demand-driven premia that reflect the view of option traders and are, in particular, informative about their knowledge of stock return anomalies. Based on a model-free decomposition of stock returns into the returns of synthetic forwards and conversion trades, we are able to separate the mechanically induced effect of stock mispricing on option prices from the price impact caused by option investors. We find that options written on mispriced stocks are mispriced as well, but to a lesser degree, which is in line with the intuition that option traders are comparatively more sophisticated. In particular, we document anomalous raw option returns caused by stock mispricing; an effect that is not present – or even reversed – in delta-hedged option returns. The structure in raw and delta-hedged option returns suggests that sophisticated option traders predominantly choose to buy put options to trade against the stock mispricing. Finally, consistent with the view that higher arbitrage frictions lead to a stronger segmentation between stock and option markets, we find that larger idiosyncratic volatility and stock illiquidity are associated with a stronger mispricing-related deviation between synthetic and actual stock prices.

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A Theoretical Model

In this section, we propose a simple, tractable model of overpriced stocks and option writing to confirm the intuition from our model-free anomaly decomposition. We consider a market with a fixed interest rate r and two stocks. The stocks have prices S and U and the same fundamental value V, which follows a geometric Brownian motion:

$$\frac{dV_t}{V_t} = \mu\, dt + \sigma\, dW_t. \tag{15}$$

There is an exogenous overpricing of stock S, which decays until $t = T$:

$$S_t = \begin{cases} e^{q(T-t)} V_t, & \text{for } 0 \le t < T, \\ V_t, & \text{for } t > T, \end{cases} \tag{16}$$

for some $q > 0$. We make the implicit assumption that there are certain frictions allowing the obvious arbitrage opportunity to persist. In addition, although option traders are able to trade in both stocks to hedge their option positions, their trading activity has no price impact on the stocks.

Restricting the market to just the stock U, this setting corresponds to the standard Black-Merton-Scholes (BMS) of Black and Scholes (1973) and Merton (1973), such that a European call (or put) option written on the correctly priced stock U with maturity date T and strike price K has the price

$$O_t^{U,K} = O_{BMS}(U_t, K, T-t), \tag{17}$$

where $O_t^{U,K}$ is the option price and $O_{BMS}(U, K, \tau)$ is the BMS pricing formula for a call (or put) option with stock price U, strike price K, and time to maturity τ.

The value of an option written on the mispriced stock S depends on the information of the option traders about the mispricing. Specifically, we assume that the option traders perceive the true value of stock S as

$$\widetilde{S}_t = e^{-\alpha q(T-t)} S_t = e^{(1-\alpha)q(T-t)} V_t, \tag{18}$$

for some fixed $\alpha \le 1$, which captures the option traders' view on the stock anomaly. In particular, if $\alpha = 1$, the option traders completely recognize the overpricing of the stock. For $\alpha \in (0,1)$, they are partially aware of the mispricing, whereas $\alpha = 0$ corresponds to the trivial case $\widetilde{S}_t = S_t$. Finally, for $\alpha < 0$, the perceived stock price $\widetilde{S}_t$ is even higher than the actual stock price.

We further assume that the option traders choose to incorporate their private view on the true stock price also in the option prices. As a result, the option-implied synthetic stock price corresponds to the perceived true stock value, $S_t^* = \widetilde{S}_t$, and the prices $O_t^{S,K}$ of options written on S contain an adjustment for the perceived mispricing:[19]

$$O_t^{S,K} = O_{BMS}(\widetilde{S}_t, K, T-t). \tag{19}$$

Consequently, in line with the model-free arguments given in Section 2, the excess returns of synthetic forwards capture the proportion of the stock overpricing that is reflected in option prices, whereas conversion trades quantify the specific reaction of the option traders to the anomaly:

$$\hat{r}_F \approx \mu T - (1-\alpha)qT, \tag{20}$$

$$\hat{r}_G^e \approx -\alpha qT. \tag{21}$$

In addition, if $\alpha \neq 0$, there is a deviation between the stock price S and the one perceived by the option traders, which results in a violation of standard no-arbitrage relations in the option market:

$$C_t^{S,K} - P_t^{S,K} - S_t + e^{-r(T-t)}K = S_t\Big(e^{-\alpha q(T-t)} - 1\Big) \neq 0 \tag{22}$$

Note that this result applies to the *standard* put-call parity, i.e., as evaluated by an (uninformed) econometrician. From the perspective of an informed option trader, put-call parity does indeed hold, as both call and put options are consistently priced for the perceived correct stock price $\widetilde{S}_t$.

As long as $\alpha < 1$, the options are mispriced as well. Call (put) options have a positive (negative) exposure to their underlying stock, so that stock overpricing increases call and decreases put option prices, with intuitive implications for raw option returns:

$$r^e_{C^S} < r^e_{C^U}, \tag{23}$$

$$r^e_{P^S} > r^e_{P^U}, \tag{24}$$

where $r_O^e = \frac{O_T - O_0}{O_0} - r(0,T)$ is the return to maturity of option O in excess of the risk-free rate $r(0,T)$. While these results are rather immediate, the impact of the mispricing on delta-hedged option returns is not as clear, as stock overpricing simultaneously influences option prices, stock prices, and deltas. Therefore, in the following, we analyze raw and delta-hedged option returns in a simulation study.

[19] Given the model structure, options on S can be hedged with the correctly priced stock U. However, if the option traders do not fully recognize the mispricing in S, they estimate a wrong hedge ratio between the two stocks, such that the options are still mispriced, consistent with the given pricing formula.

Simulation study We simulate 10 000 paths of the fundamental value V and the associated stock prices S and U based on Eqs. (15) and (16), assuming a mispricing of $q = 1\%$ that decays over one month.[20] The risk-free interest rate is set to $r = 3\%$ per year, the expected stock return is $\mu = 8\%$ and the volatility equals $\sigma = 0.2$.

Table A1 shows the resulting average returns for some benchmark scenarios. The first three cases cover completely informed ($\alpha = 1.0$), partially informed ($\alpha = 0.5$), and completely uninformed ($\alpha = 0.0$) option traders. The last two specifications, $\alpha = -1.0$ and $\alpha = -0.5$, correspond to additional overpricing in the option market. First of all, the simulation results are in line with the theoretically derived relations for synthetic forwards, conversion trades, and raw option returns. In particular, raw call (put) options written on the overpriced stock S earn lower (higher) returns as the respective options written on the correctly priced stock U, and this difference becomes smaller in magnitude for higher levels of option trader sophistication α. For $\alpha < 0$, options are even more mispriced, so that delta-hedged call (put) options also earn negative (positive) returns.[21] When option traders are aware of the mispricing, i.e., for $\alpha > 0$, raw and delta-hedged option returns have different signs, reflecting the lower degree of stock mispricing embedded in the options.

[20] This choice corresponds to a monthly return difference of about 1% between the overpriced and correctly-priced stocks, in line with the empirical results reported by Stambaugh, Yu, and Yuan (2015), for example.

[21] We consider delta-hedged option returns with time-discrete rebalancing of the hedging position, closely following the definitions given in Section 3.

Table A1: Simulation results

This table shows simulated stock and option returns, as implied by the theoretical model outlined in Appendix A. First, we simulate 10 000 paths of the correctly priced stock U and the overpriced stock S over one month and calculate the corresponding average excess returns. Based on these sample paths, we calculate average raw and delta-hedged returns of at-the-money-forward call and put options with one month to maturity. Finally, we combine the returns of calls, puts, and the stocks, to form returns of synthetic forwards and conversion trades. All returns are given in monthly percent.

		Excess returns				Delta-hedged returns		
Specification		Stock	Forward	Call	Put	Conversion	Call	Put
	Stock U	0.4^*	0.4^*	33.9^*	-26.1^*	0.0	0.0	0.0
$\alpha = 1.0$	Stock S	-0.6^*	0.4^*	33.9^*	-26.1^*	-1.0^*	93.8^*	-57.5^*
	Difference	-1.0^*	0.0	0.0	0.0	-1.0^*	93.8^*	-57.5^*
	Stock U	0.4^*	0.4^*	33.9^*	-26.1^*	0.0	0.0	0.0
$\alpha = 0.5$	Stock S	-0.6^*	-0.1^*	-6.1^*	10.3^*	-0.5^*	36.0^*	-36.4^*
	Difference	-1.0^*	-0.5^*	-40.0^*	36.4^*	-0.5^*	36.0^*	-36.4^*
	Stock U	0.4^*	0.4^*	33.9^*	-26.1^*	0.0	0.0	0.0
$\alpha = 0.0$	Stock S	-0.6^*	-0.6^*	-31.0^*	74.2^*	0.0	-0.1	0.5
	Difference	-1.0^*	-1.0^*	-64.9^*	100.3^*	0.0	-0.1	0.5
	Stock U	0.4^*	0.4^*	33.9^*	-26.1^*	0.0	0.0	0.0
$\alpha = -0.5$	Stock S	-0.6^*	-1.1^*	-47.1^*	192.0^*	0.5^*	-23.5^*	68.7^*
	Difference	-1.0^*	-1.5^*	-81.0^*	218.1^*	0.5^*	-23.5^*	68.7^*
	Stock U	0.4^*	0.4^*	33.9^*	-26.1^*	0.0	0.0	0.0
$\alpha = -1.0$	Stock S	-0.6^*	-1.6^*	-58.1^*	421.5^*	1.0^*	-39.3^*	201.6^*
	Difference	-1.0^*	-2.0^*	-92.0^*	447.6^*	1.0^*	-39.3^*	201.6^*

$^*p < 0.01$

B Further Analyses

In the following, we report additional results on the MAX anomaly in option returns:

- Table A2: MAX alphas based on alternative factor models
- Table A3: Alternative MAX measures and option portfolio returns

Table A2: MAX alphas based on alternative factor models

This table shows alphas of portfolios formed on the MAX measure of Bali, Cakici, and Whitelaw (2011), i.e., the highest daily return in the preceding month. For each stock portfolio, we consider the respective returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. In the FF6 specification, we consider the six-factor model of Fama and French (2018), i.e., the standard Fama and French (1993) factors, along with the profitability and investment factors of Fama and French (2015) and Carhart's (1997) momentum factor. The CHW alphas correspond to the factor model of Cremers, Halling, and Weinbaum (2014), which consists of the market return as well as a jump and a volatility risk factor. The final specification incorporates the three Fama and French (1993) factors, Carhart's (1997) momentum factor, as well as higher moments of stock and option market returns, as proposed by Vasquez (2017). All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Forwards			Conversions		
Portfolio	FF6	CHW	Vasquez	FF6	CHW	Vasquez
1 (low)	0.14	0.30^{***}	0.24	-0.06^{***}	-0.06^{***}	-0.05^{***}
2	-0.03	0.11	0.14	-0.06^{***}	-0.07^{***}	-0.06^{***}
3	0.04	0.14	0.11	-0.06^{***}	-0.07^{***}	-0.07^{***}
4	0.02	0.08	0.01	-0.06^{***}	-0.07^{***}	-0.07^{***}
5	0.05	0.03	-0.04	-0.07^{***}	-0.08^{***}	-0.08^{***}
6	0.15	0.12	0.16	-0.08^{***}	-0.09^{***}	-0.08^{***}
7	0.03	-0.13	-0.22	-0.10^{***}	-0.10^{***}	-0.08^{***}
8	-0.11	-0.30^{**}	0.12	-0.11^{***}	-0.11^{***}	-0.13^{***}
9	-0.31^{**}	-0.56^{***}	-0.48	-0.15^{***}	-0.16^{***}	-0.16^{***}
10 (high)	-0.41^{**}	-0.86^{***}	-0.61	-0.19^{***}	-0.20^{***}	-0.17^{***}
10–1	-0.55^{***}	-1.16^{***}	-0.85	-0.13^{***}	-0.13^{***}	-0.12^{***}
	(-2.65)	(-4.48)	(-1.40)	(-10.03)	(-9.87)	(-6.45)

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

Table A3: Alternative MAX measures and option portfolio returns

This table shows Fama and French (1993) alphas of long-short conversion and forward returns based on a decile portfolio sort on several alternative MAX measures. For reference, the first line corresponds to the original MAX measure of Bali, Cakici, and Whitelaw (2011), i.e., the highest daily return in the preceding month. As more robust alternative, we consider the second-highest return in the next specification. In the last two specifications, we define alternative MAX measures as the average of the five highest return in the preceding month and the then highest returns in the last three months, respectively. For each specification, we report the average difference in conversion and forward returns between the highest and lowest decile portfolio. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

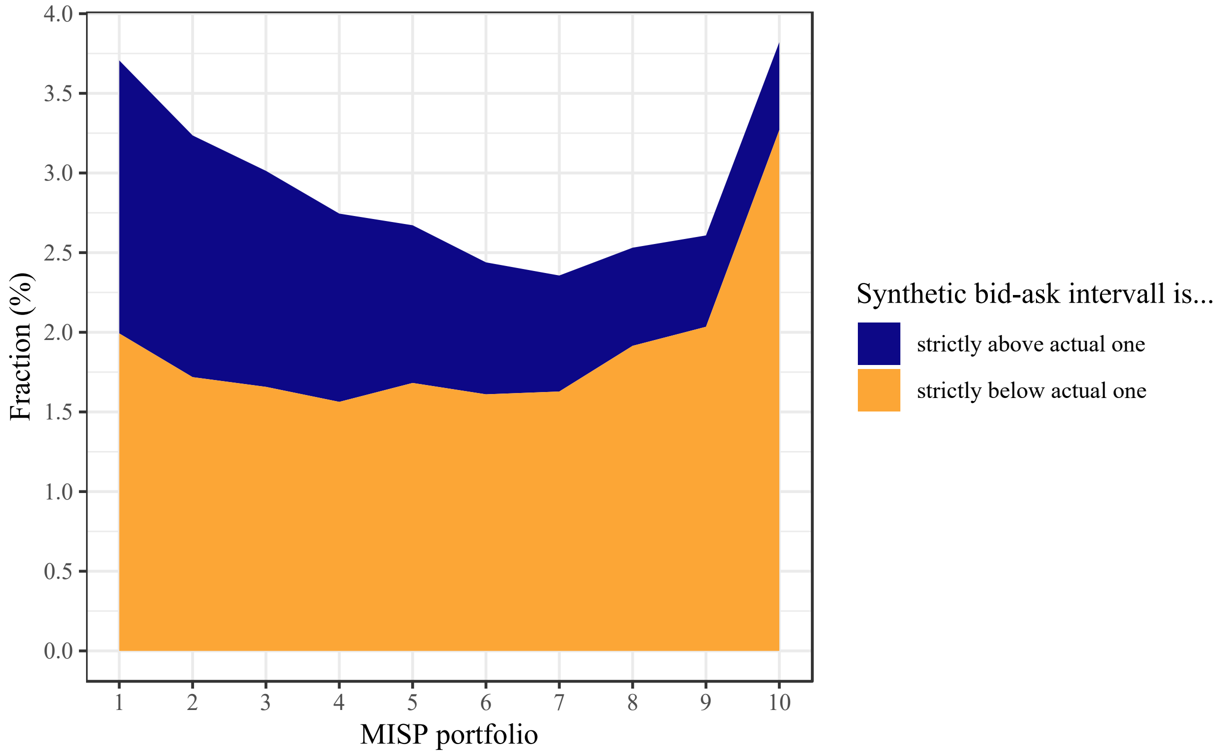
	Long-short alphas	
MAX specification	Conversions	Forwards
Highest return in last month (baseline)	-0.13^{***}	-1.15^{***}
	(-10.18)	(-4.55)
Second-highest return in last month	-0.15^{***}	-1.12^{***}
	(-9.82)	(-3.57)
Average of five highest returns in last month	-0.15^{***}	-1.21^{***}
	(-9.99)	(-3.73)
Average of ten highest returns in last three months	-0.18^{***}	-1.24^{***}
	(-10.16)	(-3.69)

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

Figures

Figure 1: Actual and synthetic bid-ask intervals

This figure visualizes potential arbitrage opportunities between actual and synthetic stock positions in monthly-rebalanced decile portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). For each stock in the portfolios, we calculate the bid-ask interval corresponding to a synthetic stock position constructed from at-the-money-forward call and put options with one month to maturity. We report the average fraction of observations per portfolio where the synthetic interval lies strictly below (orange area) and strictly above (blue area) the actual bid-ask interval, respectively.



Tables

Table 1: Descriptive statistics

This table shows descriptive statistics of our main data set. For each variable, we show the full-sample mean, standard deviation, and the 5%, 50% (median), and 95% quantile. The first three lines show our main explanatory variables: the mispricing measure of Stambaugh, Yu, and Yuan (2015) (MISP), Bali, Cakici, and Whitelaw's (2011) MAX measure, as well as idiosyncratic volatility as defined by Ang et al. (2006). On the stock-level, we analyze the firms' size, relative bid-ask spreads and the monthly excess return. For call and put options, we consider the value of open interest (given by the product of open interest and the options' mid price), the bid-ask spread relative to the options' price, as well as embedded leverage (absolute value of delta times stock prices over option price, following Frazzini and Pedersen (2012)). Finally, we include the options' excess and daily delta-hedged return, both relative to the options' price and in a leverage-adjusted version, i.e., relative to the product of absolute delta and the stock price. In addition, in the last two lines, we report statistics on the excess returns of conversion trades and synthetic forwards.

Variable	Mean	Std. dev.	5%	Median	95%
Explanatory variables					
MISP	49.31	13.25	28.77	48.58	72.46
MAX (%)	5.90	5.72	1.66	4.47	14.77
IVOL (%)	2.06	1.55	0.65	1.67	4.74
Stocks					
Firm size ($ billion)	8.14	24.30	0.26	1.93	32.12
Relative bid-ask spread (%)	0.32	0.65	0.01	0.09	1.56
Excess return (%)	0.65	13.64	−20.68	0.81	20.94
Call options					
Value of open interest ($1000)	2.15	8.50	0.01	0.30	9.25
Relative bid-ask spread (%)	23.46	24.58	3.57	15.38	70.59
Embedded leverage	13.40	7.05	5.59	11.76	26.67
Excess return (%)	7.53	171.08	−100.41	−77.48	321.41
Excess return, deleveraged (%)	0.39	16.13	−15.31	−4.27	28.48
Delta-hedged return (%)	−1.76	62.26	−70.68	−7.26	82.98
Delta-hedged return, deleveraged (%)	−0.22	5.07	−6.48	−0.59	7.12
Put options					
Value of open interest ($1000)	1.41	5.99	0.00	0.15	6.21
Relative bid-ask spread (%)	25.58	26.93	3.77	16.39	80.00
Embedded leverage	12.45	6.95	4.59	10.87	25.58
Excess return (%)	−13.18	158.14	−100.42	−100.00	287.61
Excess return, deleveraged (%)	−1.18	16.98	−18.00	−5.57	30.76
Delta-hedged return (%)	−3.44	60.77	−73.40	−8.79	81.14
Delta-hedged return, deleveraged (%)	−0.45	5.99	−8.02	−0.75	7.90
Option portfolios					
Conversion excess return (bps)	−8.79	63.42	−95.57	−3.53	62.03
Forwards excess return (%)	0.73	13.64	−20.54	0.87	21.08

Table 2: Mispricing in stocks and option portfolios

This table shows Fama and French (1993) alphas of portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). For each stock portfolio, we consider the respective stock returns, as well as the returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

Portfolio	Stocks	Forwards	Conversions	Forwards (adj.)	Conversions (adj.)
1 (low)	0.27^{**}	0.33^{***}	-0.06^{***}	0.24^{**}	0.03^{***}
2	0.23^{**}	0.29^{***}	-0.06^{***}	0.20^{**}	0.03^{***}
3	0.09	0.16^{*}	-0.07^{***}	0.07	0.02^{***}
4	0.12	0.18^{*}	-0.06^{***}	0.09	0.03^{***}
5	0.00	0.07	-0.07^{***}	-0.01	0.01^{***}
6	0.00	0.08	-0.08^{***}	-0.01	0.01^{**}
7	-0.07	0.01	-0.08^{***}	-0.08	0.01^{*}
8	-0.30^{**}	-0.20	-0.10^{***}	-0.29^{**}	-0.01^{**}
9	-0.50^{***}	-0.37^{**}	-0.13^{***}	-0.46^{***}	-0.04^{***}
10 (high)	-1.18^{***}	-1.01^{***}	-0.17^{***}	-1.09^{***}	-0.08^{***}
10–1	-1.45^{***}	-1.34^{***}	-0.11^{***}	-1.34^{***}	-0.11^{***}
	(-5.70)	(-5.21)	(-9.15)	(-5.21)	(-9.15)

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

Table 3: Value-weighted portfolios formed on stock mispricing

This table shows Fama and French (1993) alphas of portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). For each portfolio, we consider the respective stock returns, as well as the returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. The first three columns correspond to standard value-weighted portfolios, i.e., to weighting with market capitalization of the stocks. The remaining columns show results from weighting by the average value of open interest of the considered call and put options. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Market capitalization			Value of open interest		
	Stocks	Forwards	Conversions	Stocks	Forwards	Conversions
1 (low)	0.25**	0.27**	−0.02**	0.41**	0.44**	−0.02***
2	0.10	0.13	−0.03***	0.21	0.23	−0.03***
3	0.13	0.16	−0.03***	0.27	0.31	−0.03***
4	0.32***	0.34***	−0.02***	0.42**	0.46**	−0.03***
5	0.02	0.06	−0.04***	−0.04	0.02	−0.06***
6	−0.07	−0.03	−0.04***	−0.20	−0.13	−0.07***
7	−0.10	−0.06	−0.04***	−0.24	−0.16	−0.08***
8	−0.23	−0.17	−0.06***	−0.43	−0.32	−0.11***
9	−0.27	−0.21	−0.06***	−1.03***	−0.91***	−0.12***
10 (high)	−1.11***	−1.02***	−0.10***	−1.46***	−1.27***	−0.19***
10–1	−1.37***	−1.29***	−0.08***	−1.87***	−1.71***	−0.17***
	(−5.02)	(−4.74)	(−6.07)	(−3.41)	(−3.11)	(−8.71)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 4: MISP alphas based on other factor models

This table shows alphas of portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). For each stock portfolio, we consider the respective returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. In the FF6 specification, we consider the six-factor model of Fama and French (2018), i.e., the standard Fama and French (1993) factors, along with the profitability and investment factors of Fama and French (2015) and Carhart's (1997) momentum factor. The CHW alphas correspond to the factor model of Cremers, Halling, and Weinbaum (2014), which consists of the market return as well as a jump and a volatility risk factor. The final specification incorporates the three Fama and French (1993) factors, Carhart's (1997) momentum factor, as well as higher moments of stock and option market returns, as proposed by Vasquez (2017). All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Forwards			Conversions		
Portfolio	FF6	CHW	Vasquez	FF6	CHW	Vasquez
1 (low)	0.14	0.33***	−0.10	−0.06***	−0.06***	−0.06***
2	0.17	0.30***	0.24	−0.06***	−0.06***	−0.06***
3	0.09	0.17*	0.05	−0.06***	−0.07***	−0.06***
4	0.14	0.23**	0.16	−0.06***	−0.06***	−0.06***
5	0.05	0.11	0.04	−0.07***	−0.08***	−0.08***
6	0.14	0.10	0.19	−0.07***	−0.08***	−0.09***
7	0.13	0.04	0.03	−0.07***	−0.08***	−0.08***
8	−0.04	−0.19	−0.08	−0.09***	−0.10***	−0.12***
9	−0.11	−0.31*	−0.14	−0.13***	−0.13***	−0.14***
10 (high)	−0.60***	−0.92***	−0.01	−0.17***	−0.17***	−0.20***
10–1	−0.74***	−1.25***	0.09	−0.11***	−0.11***	−0.13***
	(−3.96)	(−4.94)	(0.22)	(−9.05)	(−8.95)	(−7.00)

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

Table 5: Characteristics of the MISP portfolios

This table shows several stock and option characteristics of portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). The first two rows correspond to their main explanatory variables, the MISP measure and Ang et al.'s (2006) idiosyncratic stock volatility. The second part shows the stocks' Amihud (2002) illiquidity and the relative bid-ask spreads of the stocks and options, where the latter is defined as the average of the respective relative spread of the at-the-money-forward call and put option with one month to maturity. The next part shows the average market cap and the dollar open interest of the reference options. In the last line, we report the average variance risk premium of the stock, as defined by Carr and Wu (2009). For each variable, the last column shows the average differnce between the tenth and first portfolio with significances based on Newey and West (1987) standard errors.

Portfolio	1	2	3	4	5	6	7	8	9	10	10–1
MISP	27.89	35.43	39.73	43.44	46.93	50.41	54.19	58.48	63.87	73.55	45.65^{***}
IVOL (%)	1.78	1.79	1.85	1.91	2.00	2.09	2.23	2.33	2.47	2.75	0.98^{***}
Amihud illiquidity (per $100 mn)	0.59	0.57	0.64	0.73	0.78	0.92	1.04	1.19	1.24	1.50	0.91^{***}
Stock bid-ask spread (%)	0.36	0.39	0.40	0.40	0.42	0.43	0.43	0.46	0.47	0.51	0.15^{***}
Option bid-ask spread (%)	19.28	20.00	21.15	22.49	22.61	23.37	23.81	23.76	24.56	24.66	5.37^{***}
Market cap (bn $)	16.75	13.47	11.28	9.71	7.66	6.49	5.47	4.81	4.17	3.23	-13.52^{***}
Value of call open interest ($1000)	3.28	2.76	2.62	2.33	2.00	1.97	1.82	1.77	1.73	1.68	-1.60^{***}
Value of put open interest ($1000)	2.10	1.75	1.67	1.50	1.37	1.33	1.26	1.18	1.18	1.13	-0.97^{***}
Variance risk premium (%)	0.22	0.39	0.48	0.57	0.52	0.46	0.41	−0.07	−0.91	−2.37	-2.59^{**}

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

Table 6: MISP portfolio sort conditional on the variance risk premium

This table shows results from a portfolio sort on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015), controlling for the variance risk premium (VRP). Each month, we form decile portfolios on the variance risk premium and then ten conditional MISP-portfolios. We aggregate the VRP-MISP portfolios in the VRP dimension to get ten MISP portfolios with comparable VRP levels. For each of these portfolios, we consider the respective stock returns, as well as the returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

			FF3 alpha		
Portfolio	VRP	MISP	Stocks	Forwards	Conversions
1 (low)	0.02	28.90	0.16	0.23*	−0.07***
2	−0.15	36.36	0.31***	0.39***	−0.07***
3	−0.24	40.53	0.07	0.15	−0.07***
4	−0.31	44.01	0.05	0.12	−0.07***
5	−0.17	47.26	0.16	0.24*	−0.08***
6	−0.01	50.53	0.06	0.15	−0.09***
7	−0.17	54.10	−0.11	−0.02	−0.09***
8	−0.34	58.19	−0.27*	−0.18	−0.10***
9	−0.29	63.38	−0.47***	−0.35**	−0.12***
10 (high)	−0.15	72.38	−0.97***	−0.84***	−0.13***
10–1	−0.17	43.47***	−1.13***	−1.07***	−0.06***
	(−0.73)	(135.72)	(−4.35)	(−4.09)	(−6.94)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 7: Regression analysis

This table shows results from Fama-MacBeth regressions of monthly forward and conversion returns (in basis points) on the MISP measure of Stambaugh, Yu, and Yuan (2015). The MISP measure is standardized to have zero mean and a standard deviation of one. In regressions (2), (4), and (5), we control for idiosyncratic volatility, Amihud (2002) illiquidity, the relative option bid-ask spread, firm size (defined as the logarithm of market capitalization), the logarithm of the value of open interest (defined as the sum of the respective products of option price and open interest for the call and put option), the call-put open interest ratio (i.e. call open interest relative to put open interest), and the stock-specific variance risk premium. In specification (5), we multiply the starred variables with the sign of the respective conversion return to quantify the impact on absolute conversion returns. We report time-series averages of the cross-sectional regression coefficients, along with Newey and West (1987) t-statistics.

	Forward return (bps)		Conversion return (bps)		
	(1)	(2)	(3)	(4)	(5)
MISP (std)	-24.14^{**}	-23.40^{***}	-2.88^{***}	-1.45^{***}	-1.52^{***}
	(-2.53)	(-3.10)	(-8.83)	(-6.16)	(-8.26)
IVOL*		-15.00^{**}		-2.01^{***}	7.21^{***}
		(-2.01)		(-6.22)	(17.17)
ILLIQ*		0.86		0.21	2.83^{***}
		(0.34)		(0.70)	(10.35)
Option spread (%)*		-0.11		-0.05	0.93^{***}
		(-0.17)		(-1.44)	(14.51)
Firm size*		-11.00		2.06^{***}	-1.50^{***}
		(-1.35)		(7.94)	(-11.23)
Log(OI value)*		-0.27		-1.39^{***}	2.43^{***}
		(-0.06)		(-6.99)	(10.98)
OI value call/put		-0.04		-0.02^{***}	-0.01
		(-0.41)		(-2.99)	(-1.20)
VRP		6.10		17.36^{***}	16.43^{***}
		(0.12)		(6.09)	(6.25)
Constant	83.43^{**}	271.55^{**}	-8.73^{***}	-24.52^{***}	-3.29^{***}
	(2.03)	(2.16)	(-9.92)	(-6.79)	(-11.93)
(*) signed	no	no	no	no	yes

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

Table 8: Mispricing in option returns

This table shows several types of call and put option portfolios formed on the MISP measure of Stambaugh, Yu, and Yuan (2015). For each portfolio, we report Fama and French (1993) alphas of raw (r_O) and daily delta-hedged (r_{dh}) option gains relative to the options' price. In addition, we consider leverage-adjusted returns, $\hat{r}_O$ and $\hat{r}_{dh}$, given by the respective option gains relative to the product of the options' absolute delta and the underlying stock prices. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Call options				Put options			
	Raw		Delta-hedged		Raw		Delta-hedged	
Portfolio	r_O	$\hat{r}_O$	r_{dh}	$\hat{r}_{dh}$	r_O	$\hat{r}_O$	r_{dh}	$\hat{r}_{dh}$
1 (low)	2.04	0.02	−0.33	−0.10	−8.06***	−0.69***	−1.86**	−0.25***
2	0.58	−0.08	−0.96	−0.11	−8.15***	−0.67***	−1.92*	−0.24**
3	2.23	−0.04	0.09	−0.05	−5.67**	−0.43**	−1.67*	−0.22**
4	1.48	−0.05	0.19	−0.03	−6.20**	−0.44*	−1.81*	−0.22**
5	0.91	−0.11	0.14	−0.04	−4.94*	−0.34	−2.55**	−0.28***
6	1.80	−0.05	−0.13	−0.05	−5.20**	−0.32	−2.36**	−0.29***
7	1.37	−0.11	−0.02	−0.06	−1.76	−0.17	−1.89*	−0.26**
8	−0.46	−0.39*	−0.70	−0.16*	−1.99	−0.07	−2.92***	−0.44***
9	−1.36	−0.55***	−0.14	−0.13	−0.65	0.08	−3.32***	−0.54***
10 (high)	−4.29*	−1.02***	−0.17	−0.18	4.48	0.86**	−3.43***	−0.69***
10–1	−6.34***	−1.04***	0.15	−0.09	12.55***	1.55***	−1.57**	−0.43***
	(−2.94)	(−3.85)	(0.18)	(−0.89)	(5.40)	(4.62)	(−2.02)	(−3.72)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 9: MAX effect in stocks and option portfolios

This table shows Fama and French (1993) alphas of portfolios formed on the MAX measure of Bali, Cakici, and Whitelaw (2011), i.e., the highest daily return in the preceding month. For each stock portfolio, we consider the respective stock returns, as well as the returns of synthetic forwards and conversion trades constructed from the corresponding at-the-money-forward call and put options with one month to maturity. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

Portfolio	Stocks	Forwards	Conversions	Forwards (adj.)	Conversions (adj.)
1 (low)	0.22^{**}	0.28^{**}	-0.06^{***}	0.18^{*}	0.04^{***}
2	0.05	0.11	-0.06^{***}	0.02	0.03^{***}
3	0.06	0.13	-0.07^{***}	0.03	0.03^{***}
4	0.00	0.07	-0.06^{***}	-0.03	0.03^{***}
5	-0.07	0.00	-0.07^{***}	-0.09	0.02^{***}
6	0.00	0.08	-0.09^{***}	-0.01	0.01^{**}
7	-0.24^{**}	-0.14	-0.10^{***}	-0.23^{**}	0.00
8	-0.43^{***}	-0.32^{***}	-0.11^{***}	-0.42^{***}	-0.02^{***}
9	-0.75^{***}	-0.60^{***}	-0.15^{***}	-0.70^{***}	-0.05^{***}
10 (high)	-1.07^{***}	-0.88^{***}	-0.19^{***}	-0.97^{***}	-0.10^{***}
10–1	-1.28^{***}	-1.15^{***}	-0.13^{***}	-1.15^{***}	-0.13^{***}
	(-5.11)	(-4.55)	(-10.18)	(-4.55)	(-10.18)

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

Table 10: MAX effect in option returns

This table shows several types of call and put option portfolios formed on the MAX measure of Bali, Cakici, and Whitelaw (2011), i.e., the highest daily return in the preceding month. For each portfolio, we report Fama and French (1993) alphas of raw (r_O) and daily delta-hedged (r_{dh}) option gains relative to the options' price. In addition, we consider leverage-adjusted returns, $\hat{r}_O$ and $\hat{r}_{dh}$, given by the respective option gains relative to the product of the options' absolute delta and the underlying stock prices. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Call options				Put options			
	Raw		Delta-hedged		Raw		Delta-hedged	
Portfolio	r_O	$\hat{r}_O$	r_{dh}	$\hat{r}_{dh}$	r_O	$\hat{r}_O$	r_{dh}	$\hat{r}_{dh}$
1 (low)	5.61^{*}	0.09	−1.31	-0.14^{**}	-9.94^{***}	-0.53^{***}	-3.85^{***}	-0.33^{***}
2	2.55	−0.02	−0.57	−0.11	-5.37^{*}	−0.26	-2.72^{***}	-0.28^{***}
3	3.22	0.02	−0.33	−0.09	−4.89	−0.27	-2.46^{**}	-0.28^{***}
4	1.23	−0.11	0.05	−0.08	-5.53^{**}	−0.36	-2.35^{**}	-0.30^{***}
5	1.57	−0.08	−0.05	−0.09	−2.78	−0.14	-2.03^{**}	-0.30^{***}
6	0.99	−0.09	0.33	−0.05	-4.21^{*}	−0.35	-2.28^{**}	-0.30^{***}
7	−0.23	−0.31	0.14	−0.07	−0.90	−0.09	-1.50^{*}	-0.33^{***}
8	−1.77	-0.48^{**}	0.28	−0.03	−0.44	0.07	-2.43^{***}	-0.40^{***}
9	−3.70	-0.78^{***}	0.26	−0.07	0.83	0.34	-2.63^{***}	-0.48^{***}
10 (high)	-6.55^{***}	-1.24^{***}	−0.79	-0.20^{*}	−0.52	0.39	-4.52^{***}	-0.81^{***}
10–1	-12.16^{***}	-1.33^{***}	0.53	−0.06	9.42^{***}	0.92^{***}	−0.67	-0.48^{***}
	(−4.29)	(−4.38)	(0.57)	(−0.68)	(3.28)	(2.92)	(−0.74)	(−4.38)

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

Table 11: Effects of mispricing and idiosyncratic volatility in forwards and conversion returns

This table shows Fama and French (1993) alphas of double-sorted stock portfolios. Each month, we first form five portfolios on idiosyncratic volatility. Within each of these portfolios, we then form five portfolios on the MISP measure of Stambaugh, Yu, and Yuan (2015). In Panel A, we report the alphas of synthetic forward returns, Panel B shows the corresponding returns of conversion trades, both constructed from the at-the-money-forward call and put options with one month to maturity. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

Panel A: Forwards

	IVOL portfolio					
MISP portfolio	1 (low)	2	3	4	5 (high)	5–1
1 (low)	0.29^{**}	0.35^{***}	0.58^{***}	0.14	0.03	-0.26
						(-0.97)
2	0.25^{**}	0.25^{*}	0.25^{*}	-0.13	-0.58^{**}	-0.83^{***}
						(-2.88)
3	0.27^{**}	0.28^{**}	0.23	0.22	-0.43^{*}	-0.70^{**}
						(-2.54)
4	0.27^{*}	0.23^{*}	0.17	-0.26	-0.86^{***}	-1.14^{***}
						(-3.90)
5 (high)	-0.14	-0.07	-0.38^{**}	-0.72^{***}	-1.43^{***}	-1.29^{***}
						(-4.24)
5–1	-0.43^{**}	-0.43^{**}	-0.97^{***}	-0.85^{***}	-1.45^{***}	-1.03^{***}
	(-2.46)	(-2.23)	(-3.75)	(-2.75)	(-3.95)	(-2.85)

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

Panel B: Conversions

	IVOL portfolio					
MISP portfolio	1 (low)	2	3	4	5 (high)	5–1
1 (low)	-0.04^{***}	-0.05^{***}	-0.05^{***}	-0.08^{***}	-0.11^{***}	-0.07^{***}
						(-5.26)
2	-0.05^{***}	-0.05^{***}	-0.05^{***}	-0.08^{***}	-0.11^{***}	-0.07^{***}
						(-5.26)
3	-0.05^{***}	-0.05^{***}	-0.07^{***}	-0.08^{***}	-0.13^{***}	-0.08^{***}
						(-5.68)
4	-0.06^{***}	-0.07^{***}	-0.07^{***}	-0.09^{***}	-0.21^{***}	-0.15^{***}
						(-7.87)
5 (high)	-0.07^{***}	-0.08^{***}	-0.10^{***}	-0.13^{***}	-0.25^{***}	-0.19^{***}
						(-9.25)
5–1	-0.02^{***}	-0.03^{***}	-0.05^{***}	-0.05^{***}	-0.14^{***}	-0.12^{***}
	(-3.92)	(-4.75)	(-5.17)	(-4.35)	(-7.61)	(-6.27)

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

Table 12: Effects of mispricing and stock illiquidity in forwards and conversion returns

This table shows Fama and French (1993) alphas of double-sorted stock portfolios. Each month, we first form five portfolios on Amihud (2002) illiquidity. Within each of these portfolios, we then form five portfolios on the MISP measure of Stambaugh, Yu, and Yuan (2015). In Panel A, we report the alphas of synthetic forward returns, Panel B shows the corresponding returns of conversion trades, both constructed from the at-the-money-forward call and put options with one month to maturity. All alphas are given in monthly percent, significances are based on Newey and West (1987) standard errors.

Panel A: Forwards

	ILLIQ portfolio					
MISP portfolio	1 (low)	2	3	4	5 (high)	5–1
1 (low)	0.32^{**}	0.40^{***}	0.28^{*}	0.35^{**}	−0.11	-0.43^{*}
						(−1.89)
2	0.36^{***}	0.32^{**}	0.23	0.27	−0.16	-0.52^{**}
						(−2.16)
3	0.27^{**}	0.28^{**}	0.03	0.19	−0.22	-0.49^{**}
						(−2.29)
4	0.06	0.15	0.06	0.07	−0.20	−0.26
						(−1.08)
5 (high)	-0.46^{***}	-0.74^{***}	-0.69^{***}	-0.61^{***}	−0.14	0.32
						(1.06)
5–1	-0.78^{***}	-1.15^{***}	-0.97^{***}	-0.96^{***}	−0.03	0.75^{**}
	(−3.19)	(−4.33)	(−2.93)	(−3.56)	(−0.11)	(2.20)

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

Panel B: Conversions

	ILLIQ portfolio					
MISP portfolio	1 (low)	2	3	4	5 (high)	5–1
1 (low)	-0.02^{***}	-0.06^{***}	-0.08^{***}	-0.09^{***}	-0.09^{***}	-0.06^{***}
						(−4.00)
2	-0.03^{***}	-0.06^{***}	-0.08^{***}	-0.09^{***}	-0.09^{***}	-0.06^{***}
						(−3.11)
3	-0.03^{***}	-0.06^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.06^{***}
						(−3.28)
4	-0.04^{***}	-0.07^{***}	-0.09^{***}	-0.12^{***}	-0.12^{***}	-0.09^{***}
						(−4.72)
5 (high)	-0.05^{***}	-0.09^{***}	-0.12^{***}	-0.14^{***}	-0.26^{***}	-0.21^{***}
						(−10.20)
5–1	-0.03^{***}	-0.03^{***}	-0.04^{***}	-0.05^{***}	-0.17^{***}	-0.14^{***}
	(−5.47)	(−3.20)	(−3.63)	(−3.76)	(−8.38)	(−7.28)

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

Table 13: Regression analysis of mispricing and arbitrage frictions

This table shows results from Fama-MacBeth regressions of monthly forward and conversion returns (in basis points) on the MISP measure of Stambaugh, Yu, and Yuan (2015), idiosyncratic volatility (IVOL), Amihud (2002) illiquidity (ILLIQ), and their interaction. All variables are standardized to have zero mean and a standard deviation of one. We report time-series averages of the cross-sectional regression coefficients, along with Newey and West (1987) t-statistics.

	Forward return (bps)			Conversion return (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)
MISP (std)	-12.81	-25.38^{***}	-13.77^{*}	-2.26^{***}	-2.84^{***}	-2.09^{***}
	(-1.64)	(-2.62)	(-1.77)	(-7.57)	(-8.46)	(-7.02)
IVOL (std)	-9.86		-11.30	-4.39^{***}		-4.13^{***}
	(-0.64)		(-0.73)	(-8.63)		(-8.10)
MISP × IVOL	-13.23^{**}		-13.40^{**}	-1.45^{***}		-1.60^{***}
	(-2.35)		(-2.38)	(-4.84)		(-5.10)
ILLIQ (std)		-1.33	-1.38		-1.35	-0.06
		(-0.10)	(-0.10)		(-0.99)	(-0.04)
MISP × ILLIQ		7.04	9.22		-3.11^{***}	-2.59^{***}
		(0.84)	(0.91)		(-3.76)	(-2.78)
IVOL × ILLIQ			-13.55			1.71
			(-0.72)			(1.47)
MISP × IVOL × ILLIQ			12.99			-2.56^{**}
			(0.86)			(-2.33)
Constant	80.28^{**}	82.41^{**}	80.82^{**}	-8.80^{***}	-8.70^{***}	-8.76^{***}
	(2.04)	(1.99)	(2.03)	(-11.42)	(-9.98)	(-11.23)

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

Table 14: Trading against stock mispricing and transaction costs

This table shows average excess returns of portfolios formed on the stock-specific MISP measure of Stambaugh, Yu, and Yuan (2015). For each portfolio, we consider reverse conversion trades, i.e., a short stock position and a long synthetic forward, constructed from the corresponding at-the-money-forward call and put options with one month to maturity. All returns are given in monthly percent, significances are based on Newey and West (1987) standard errors.

	Reverse conversions					
Portfolio	$\delta = 0\%$	$\delta = 10\%$	$\delta = 15\%$	$\delta = 25\%$	$\delta = 50\%$	$\delta = 100\%$
1 (low)	0.06^{***}	-0.04^{***}	-0.08^{***}	-0.18^{***}	-0.41^{***}	-0.89^{***}
2	0.06^{***}	-0.04^{***}	-0.09^{***}	-0.19^{***}	-0.43^{***}	-0.94^{***}
3	0.06^{***}	-0.04^{***}	-0.09^{***}	-0.20^{***}	-0.46^{***}	-1.00^{***}
4	0.06^{***}	-0.06^{***}	-0.11^{***}	-0.22^{***}	-0.51^{***}	-1.09^{***}
5	0.07^{***}	-0.05^{***}	-0.11^{***}	-0.22^{***}	-0.52^{***}	-1.13^{***}
6	0.07^{***}	-0.05^{***}	-0.12^{***}	-0.24^{***}	-0.56^{***}	-1.20^{***}
7	0.07^{***}	-0.06^{***}	-0.12^{***}	-0.26^{***}	-0.59^{***}	-1.27^{***}
8	0.09^{***}	-0.05^{***}	-0.11^{***}	-0.25^{***}	-0.60^{***}	-1.31^{***}
9	0.12^{***}	-0.03^{***}	-0.11^{***}	-0.26^{***}	-0.64^{***}	-1.42^{***}
10 (high)	0.16^{***}	-0.01	-0.10^{***}	-0.27^{***}	-0.70^{***}	-1.57^{***}
10–1	0.10^{***}	0.02^{**}	-0.01	-0.09^{***}	-0.28^{***}	-0.68^{***}
	(8.66)	(2.45)	(-1.30)	(-6.89)	(-11.32)	(-12.45)

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