Cheap Options Are Expensive

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Abstract

We show that (partial) inattention to the underlying stock prices generates a demand pressure for options on low-priced stocks, resulting in overpricing of such options. Empirically, we find that delta-hedged options on low-priced stocks underperform those on high-priced stocks by 0.54% per week for calls and 0.34% for puts. Natural experiments corroborate this finding; options tend to become relatively more expensive following stock splits, and options on mini-indices are overpriced relative to options written on otherwise identical regular indices. Skewness preference does not explain our results.

Keywords: Option returns; Investor inattention; Demand pressure

JEL Classification Numbers: G13, G14.

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The idea that attention is a scarce cognitive resource and individuals are endowed with limited attention goes back to Kahneman (1973). Since then a growing literature has examined the effect of limited attention on financial markets and asset prices. On the theoretical side, Hirshliefer, Lim, and Teoh (2011), Hirshleifer and Teoh (2003), Peng (2005), Peng and Xiong (2006), and Kacpercyzk, Van Niuwerburgh, and Veldkamp (2016) model the effects of limited attention on various aspects of financial reporting and asset price dynamics. On the empirical side, Barber and Odean (2008), Corwin and Coughenour (2008), Dellavigna and Pollet (2009), and Hirshliefer, Lim, and Teoh (2009), amongst others, show how inattention leads to investors trading behavior in settings as diverse as NYSE specialists and earnings surprises.[1] In this paper we show that inattention to an asset can result in mispricing of a *different* (albeit closely related) asset. In particular, we analyze the impact of inattention to the underlying stock price on options on that stock. We show that (partial) inattention to the underlying stock price makes an investor perceive options on low-priced stocks as cheap or "good deals," and perceive options on high-priced stocks as expensive. This leads to options written on low-priced stocks as being overpriced and having low future realized returns.

A reasonable question is why would an option trader not pay full attention to underlying stock price, as it is part of publicly available information.[2] We argue that limited attention can arise for a variety of reasons. Trading portfolios of options across multiple stocks and paying full attention to all underlying stock prices requires significant mental resources. To compound this problem, underlying prices are constantly changing and keeping track of those changes in real time puts an additional strain on attention. Barber and Odean (2008), Fang and Peress (2009), and Tetlock (2011) find that investors react to stocks just because they are 'in the news.' Furthermore, there is evidence that reference price points and anchoring play a role in pricing (Kahneman and Tversky (1979) and Shefrin and Statman (1985)). In our setting, it is conceivable that an option investor might not remember the real time prices of all underlying stocks in her portfolio, but generally remember the distribution of the underlying prices; the mean of this distribution then acts as an anchor. We hasten to add that we do not argue that there is a large number of inattentive investors in the market and inattention to underlying stock prices is a widespread phenomenon. On the contrary, we show theoretically that even a limited degree of inattention can lead to economically

[1] There is also a growing literature that analyzes the impact of news and media on financial prices. See, for example, Ben-Raphael, Da, and Israelsen (2017), Da, Engelberg, and Gao (2011), Dougal, Engelberg, Garcia, and Parsons (2012), Engelberg and Parsons (2011), Fang and Peress (2009), Fedyk (2020), and Tetlock (2007, 2011).

[2] There is evidence that investors ignore easily retrievable public information. See, for example, Huberman and Regev (2001) and Rashes (2011).

meaningful option mispricing.

We start our analysis by building a theoretical model that features three types of option traders: retail investors with only partial attention to underlying stock prices, fully rational retail investors (those with full attention), and market makers. All market participants submit limit orders for at-the-money (ATM) options, markets clear and the equilibrium option price is determined. After that, retail investors (both rational and those with limited attention) hold their option positions unhedged until maturity while market makers hedge their positions by trading the underlying stock. As in Gârleanu, Pedersen, and Poteshman (2009, henceforth GPP), hedging costs prevent the market makers from being able to hedge perfectly and make their portfolios risky. We solve for the market makers' optimal hedging policy explicitly and derive the equilibrium option price.

The model generates a number of important results. First, in equilibrium, the options on low-priced stocks are overpriced while options on high-priced stocks are underpriced. Limited attention investors have a biased perception of the actual stock price and have a prior anchor based on the distribution of all stock prices in the economy. This bias generates demand pressure for options on low-priced stocks, which makes them overpriced. Second, we show that the magnitude of mispricing is asymmetric and is stronger for low-priced stocks. Third, mispricing is increasing in the level of inattention in the market, proxied in the model by the relative number of inattentive investors and the noisiness of their signal. Mispricing is also inversely related to their risk-aversion, as more risk-averse investors participate less actively in trading. Finally, we show that mispricing is decreasing in the hedging costs faced by market makers. Imperfect hedging generates uncertainty in market makers' payoff and hence prevents them from being able to fully correct mispricing (due to their risk-aversion).

In our empirical results, we start by constructing delta-hedged call and put decile portfolios sorted on the underlying stock price. Our sample covers U.S. equity options on individual stocks during the period from 1996 to 2017. We find that portfolio returns as well as alphas from factor models increase in the underlying stock prices. For example, the return on the long-short portfolio that is long in delta-hedged calls on stocks with high price and short in delta-hedged calls on stocks with low price is 0.54% per week. We risk-adjust using a factor model that includes both stock factors (Fama and French (2015) factors and a momentum factor) as well as an option factor from Coval and Shumway (2001). Alpha from this 7-factor model is 0.44% per week. Delta-hedged put portfolios show similar patterns (long-short return and alpha of 0.34% and 0.29%, respectively). We also find support for the second implication of our model, viz. the non-linear effect of underlying price on option prices, as most of the magnitude of the long-short spreads is derived from decile one with options on lowest-priced stocks.

We test whether this pattern can be explained by the correlation of stock price with other stock characteristics. We do double sorts on stock price and characteristics such as size, book-to-market, profitability, past stock return, forecast dispersion, and net issuance. These characteristics are shown by Cao, Han, Tong, and Zhan (2017) to be useful for predicting option returns. While the magnitude of long-short returns is reduced compared to the baseline results, we still find 7-factor alphas in the range of 0.17% to 0.44% (statistically significant in all cases). We also confirm the relation between delta-hedged returns and underlying price via Fama and MacBeth (1973) (FM) regressions. Even after controlling for additional variables related to option greeks, the coefficient on (log) stock price is negative and statistically significant for both delta-hedged calls and puts. This effect is also economically large as the returns to delta-hedged call portfolios increase by 0.52% per week when the underlying stock price moves by one standard deviation.

Although we sort on the underlying stock price and not directly on option price, our results are related to a separate strand of literature that documents the impact of nominal price level on asset returns (see, for example, Bali and Murray (2013), Birru and Wang (2016), Boyer, Mitton, and Vorkink (2010), Kumar (2009), and Schutlz (2000)). The leading explanation in this literature for excessive preference for low-priced assets derives from high skewness of their returns.[3] Of immediate relevance to us, for calls on lottery-like stocks, Blau, Bowles, and Whitby (2016) show higher trading volume (quantity effect), and Byun and Kim (2016) show low returns (price effect).

We, however, formally rule out skewness preference as a driver of our results in three different ways. First, in portfolio double sorts, where we control for stock lottery characteristics (idiosyncratic skewness and the maximum-return (MAX) variable of Bali, Cakici, and Whitelaw (2011)), we find that long-short return of portfolios sorted on underlying stock price is significant for most of the skewness quintiles. Second, we explicitly control for skewness characteristics in FM regressions and find that the coefficient on (log) stock price remains negative and statistically significant. Third, and perhaps most important, we find that realized skewness of delta-hedged options on low-priced stocks is not higher (and in some cases lower) than that of delta-hedged options on high-priced stocks. It is important to note also that our results are strong for both call and put portfolios, while investors seeking to enhance skewness are likely to trade calls, and not puts, on lottery-like stocks (buying calls on lottery-like stocks is likely to further enhance skewness, while puts on such stocks

[3]Preference for skewness may be rational as in Arditti (1967), Barberis and Huang (2008), Harvey and Siddique (2000), Kraus and Litzenberger (1976), Mitton and Vorkink (2007), and Scott and Horvath (1980). Alternatively, investors may have behavioral preferences for lottery-like assets (for which low prices are a proxy) with skewed payoffs. For example, Bali, Cakici, and Whitelaw (2011), Green and Hwang (2009), and Kumar (2009) show that lottery-like stocks are overpriced and have low returns.

become worthless when the stock generates its lottery-like payoff). Finally, as we describe later, we find corroborating evidence for mini-index options, where the skewness of returns is identical for the regular and the mini-index.[4]

Transaction costs in option markets are high (Figlewski (1989) and Ofek, Richardson, and Whitelaw (2004)). Our baseline results are based on transactions at the midpoint of bid and ask quotes; in other words, at zero effective spread. We consider alternative transaction prices by changing the ratio of effective spread to quoted spread. We find that our strategy is still profitable for effective spreads of 50% (40%) of quoted spreads for calls (puts).[5]

We analyze two quasi-natural experiments to further examine the impact of underlying price on option returns. First, we analyze the effect of stock splits on option prices. Stock splits provide a unique opportunity to study the effect of a change in the underlying price on the prices of options, while keeping everything else constant. The option price should scale proportional to the underlying stock price following a split. However, if investors pay excessive attention to lower prices following a split, then one would observe option overpricing following a split. We find evidence consistent with the latter hypothesis. For example, calls (puts) are relatively 13% (9%) more expensive compared to their pre-split prices in the three-day window following the split. We also find positive coefficient on the split ratio in a panel regression of option returns around event windows.

Second, we complement the stock split evidence by analyzing mini-index options traded on both Nasdaq 100 and S&P 500 mini-indices (whose prices are one tenth of the prices of the original indices). The existence of mini index options offers a unique opportunity to examine the hypothesis of investors preferences for options on securities with low underlying prices. Absent any such preferences the prices of mini index options should be one tenth of the prices of the regular index options (as the only difference between the regular and mini indexes is the scaling factor). We find that mini index options are relatively overpriced, again pointing towards investors' preferences for options written on securities with low prices. ATM calls (puts) are 0.5% (1.2%) more expensive on mini indices than on main indices. The magnitudes of over-pricing are small as is to be expected given the high liquidity of these options. Nevertheless, the results are strongly statistically significant and suggest that investors' biases manifest themselves even for index options. It is also useful to note that skewness preference cannot explain our evidence on mini-indices.

Our model predicts that the magnitude of mispricing is positively related to the degree

[4]We do not claim that skewness preference does not manifest itself at all in options. For example, Boyer and Vorkink (2014) report relationship between ex-ante skewness and option returns. Our contention is only that skewness preference does not have the potential to explain our results.

[5]Muravyev and Pearson (2020) argue that effective spreads are around 30% of quoted spreads for traders who time their executions.

of inattention in the market. Conventional wisdom and prior studies suggest that retail investors are less sophisticated and hence potentially more inattentive to relevant information than professional investors. We use two proxies for investor sophistication. First, we argue that options written on stocks with high institutional ownership are likely to attract higher attention from more sophisticated institutional investors. Consistent with our intuition, we find a stronger effect of the underlying price on option values for options written on stocks with lower institutional ownership. Second, we classify option traders into retail and institutional using daily records of option buy and sell activity of different market participants. We then run FM regressions of net option buys from different categories of investors on the underlying stock price. We find that professional option traders buying of options (both calls and puts) increases with the underlying price. In contrast, retail option traders buying is inversely related to the stock price. In additional tests, we focus on net investor demand, measured as net open interest. In our model, demand from inattentive investors has an impact on option prices because option market makers cannot perfectly hedge their inventories. GPP (2009) suggest that weighting the net demand by option greeks, such as gamma and vega, captures the unhedgeable risks. We find that the expensiveness of options on low-priced stocks is indeed related to various measures of net option demand (raw or weighted) from retail investors. We take the totality of this evidence to be supportive of our hypothesis that the mispricing of options that we identify is likely driven by less sophisticated retail investors.

Another prediction of the model is the effect of hedging costs on the magnitude of mispricing. In the model, hedging costs result in imperfect hedging for market makers and hence their inability to fully eliminate mispricing due to their risk-aversion. Therefore, we expect a positive relation between hedging costs and the degree of mispricing. To test this prediction we double sort option portfolios on the underlying price and proxies for hedging costs. We use three such proxies: stock bid-ask spread (measured by the average daily bid-ask spread in the previous month), stock illiquidity, and idiosyncratic volatility. Consistent with the model, the 7-factor alpha of the high-minus-low stock price portfolio is generally increasing when moving from the low to the high hedging costs quintile. In all cases the alpha of the high hedging cost quintile is at least twice as much than that of the low hedging cost quintile.

As mentioned in the beginning of this introduction, we draw inspiration from the literature on the effect of limited attention on financial markets. Additionally, our paper is related to three other streams of literature. First, our paper contributes to the literature that analyzes mispricing in the options market. The usual objective in these studies is to identify an option- or stock-specific characteristic that signals over- or under-pricing in the cross-section of options. Some examples include An, Ang, Bali, and Cakici (2014), Bali and

Murray (2013), Cao and Han (2013), Cao et al. (2017), Goyal and Saretto (2009), Jones and Shemesh (2018), and Vasquez (2017). We explore a previously undocumented anomaly in option prices and returns. Unlike most of the existing studies, we offer a specific behavioral mechanism that gives rise to this anomaly. We argue that the effect of underlying stock prices on option mispricing is driven by investors' failure to fully account for the underlying prices when valuing options.

Second, our paper is related to the literature that analyzes the importance of nominal stock prices for asset returns. Shue and Townsend (2019) examine the effect of non-proportional thinking on stock return volatility, betas, and reaction to firm-specific news. Birru and Wang (2016) posit that investors overestimate the skewness of low-priced stocks and find that out-of-the-money (OTM) calls (but not OTM puts) on low-priced stocks are overpriced. In contrast, we find evidence of overpricing for both calls and puts on low-priced stocks. Blau, Bowles, and Whitby (2016) and Byun and Kim (2016) show demand and price effects on calls on lottery stocks. We find evidence of overpricing for both calls and puts on low-priced stocks and, as mentioned earlier, rule out skewness as a driver of our results. Finally, Boyer and Vorkink (2014) find evidence of skewness preference in options. Our study complements theirs by showing that option investors also exhibit a different type of behavioral bias.

Finally, our paper is related to studies of demand-based option pricing. Our theoretical model builds on GPP (2009) who show that the inability of risk-averse option market-makers to perfectly hedge their inventories has an impact on option prices. Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) show that re-hedging of option positions just before expiration produces measurable changes in stock price, and Ni, Pearson, Poteshman, and White (2021) show that option market maker rebalancing impacts stock return volatility. We complement these studies by showing that hedging costs of option market makers coupled with partial inattention of less sophisticated investors to underlying stock prices have a first-order impact on option prices.

The rest of the paper proceeds as follows. Section 1 lays down the theoretical model that forms the basis of our empirical work (proofs are relegated to Appendix A). Section 2 describes our data sources, construction of the main variables, and presents the main results. Section 3 presents results on quasi-natural experiments of stock splits and mini-index options. We investigate the role of retail investors and hedging costs in contributing to mispricing of options in Section 4 and conclude in Section 5. Internet Appendix IA.1 contains a battery of robustness tests.

1 Model

We construct an analytically tractable model of an economy where some agents have limited attention while other agents are fully rational. In general, inattention can be broadly classified as "rational" or "neglective." In the former class of models, investors are aware of attention constraints and optimally allocate attention across various assets. Rational inattention models take their roots in Merton (1987), who models that investors trade a stock only if they know it. See also Peng (2005), Peng and Xiong (2006), and Kacpercyzk, Van Niuwerburgh, and Veldkamp (2016) for models of optimal attention allocation. The mechanism in our paper is closer to the neglective inattention literature. Examples include Tetlock (2011), who argues that investors are not attentive to the staleness of information, and Da, Gurun, and Warachka (2014), who show how inattentiveness to small signals gives rise to momentum in stock returns. See also Hirshleifer, Lim, and Teoh (2011), who design a model to demonstrate how limited attention leads to various earnings-related anomalies.

We demonstrate that in equilibrium options written on stocks with lower prices are overvalued and options on stocks with higher prices are undervalued. There are three periods in the model. At time $t = 0$ agents submit their orders. Immediately after, at time $t = 0^+$ markets clear and the equilibrium price is established. Finally, at time $t = T$ the option matures and the payoffs are realized. In our model, we focus on the mispricing of call options, but our model applies in the same manner to put options.

1.1 The Economy

There are three tradeable assets in the economy: a stock, a European ATM call option written on the stock, and a risk free asset. The model can be potentially extended to incorporate American style options but at the cost of analytical tractability. The stock price process is assumed to be a standard geometric Brownian motion with drift μ and volatility σ. Without loss of generality, we normalize the riskfree rate to be zero. The economy has a finite time horizon T when the option expires. The Black and Scholes (1973) price of the ATM call at time $t = 0$ is $v_0 = \theta_0 S_0$, where S_0 is the stock price at time 0, and $\theta_0(\sigma, T)$ is a factor depending on stock volatility σ and maturity T.

The economy features three types of agents: rational agents, R (with a total number of N_R), limited-attention agents, LA (with a total number of N_L) who do not observe the price of the underlying stock exactly, and market makers, MMs (with a total number of N_M) who provide liquidity and set the market clearing price. We assume that N_R, N_L and N_M are finite but large numbers. The first two types of agents can be viewed as end-users and the third as dealers following GPP (2009). All agents are assumed to be price takers, risk averse mean-variance optimizing traders who submit price contingent limit orders (see, for example, de Jong and Rindi (2009), Grossman and Stiglitz (1980), and Hellwig (1980)).

The important mechanism that drives mispricing in our model is partial inattention to the underlying stock price. In particular, we assume that the R agents and MMs observe the stock price precisely. By contrast, the LA agents do not pay full attention to the underlying stock price. We model limited attention in a Bayesian learning framework. Specifically, we assume that the stock price S_0 is a draw from a commonly known prior lognormal distribution, $\ln S_0 \sim N\left(\ln \overline{S},\, \sigma_0^2\right)$. For example, this can be interpreted as the distribution of the prices of all stocks in the economy with listed options. In addition, each of the LA agents observes a private signal $\ln S_{L,j} = \ln S_0 + \sigma_\epsilon \epsilon_j$ about the underlying stock price, where the volatility σ_ϵ measures the level of inattention (assumed to be the same across all LA agents), and $\epsilon_j \sim N(0,\, 1)$ is i.i.d. and uncorrelated across LA agents. Higher levels of σ_ϵ indicate greater inattention. In the real world, inattention can potentially arise due to having to trade multiple assets simultaneously as well as the fact that stock prices can vary substantially over time. Then, each of the LA agents' best estimate $\widehat{S}_{0,j}$ of the initial stock price S_0 and its posterior variance σ_L^2 are given by:

$$\ln \widehat{S}_{0,j} = (1-k)\ln \overline{S} + k \ln S_{L,j}, \tag{1}$$

with $k = \left(1 + \sigma_\epsilon^2/\sigma_0^2\right)^{-1}$, and $\sigma_L^2 = \sigma_0^2 \sigma_\epsilon^2/(\sigma_0^2 + \sigma_\epsilon^2)$.

It follows that in each of the LA agents information set, the posterior distribution of S_0 is still lognormal, $\ln S_0 \sim N\left(\ln \widehat{S}_{0,j},\, \sigma_L^2\right)$, so

$$S_0 = \widehat{S}_{0,j} e^{\sigma_L u_j}, \tag{2}$$

where u_j follows the standard normal distribution.

1.2 Trading strategies of end users

At time $t = 0$, both R and LA agents submit their limit orders for the options maturing at $t = T$. These agents only trade once (at time $t = 0^+$), do not hedge their option positions, and receive their final payoffs at the maturity date of the options at time T. Their mean-variance utility is given by:

$$\mathrm{U}(y) = y(\mathrm{E}(v_T) - P_0) - \frac{1}{2}\alpha y^2 \mathrm{Var}(v_T), \tag{3}$$

where α is the risk aversion coefficient, y is the demand for the option, $\mathrm{E}(v_T)$ and $\mathrm{Var}(v_T)$ are the mean and the variance of payoff at time T based on the trader's information set at time 0, and P_0 is the equilibrium price of the option at time 0. The first-order condition yields the optimal strategy in the form of the limit order:

$$y(P_0) = \frac{\mathrm{E}(v_T) - P_0}{\alpha \mathrm{Var}(v_T)}. \tag{4}$$

As we discuss above, the two types of agents differ in their information sets at time 0. R agents observe the stock price S_0 perfectly while LA agents observe it with noise. We show in Appendix A that these agents' estimates of the mean and variance of the option payoffs are given by:

$$\begin{aligned}
\mathrm{E}_R(v_T) &= \mathrm{E}\left[(S_T - K)^+ \,|S_0\right] = S_0\, \theta_R(\mu, \sigma, T), \\
\mathrm{E}_{L,j}(v_T) &= \mathrm{E}\left[(S_T - K)^+ \,|S_{L,j}\right] = \widehat{S}_{0,j} \theta_L(\mu, \sigma, T), \\
\mathrm{Var}_R(v_T) &= \mathrm{Var}\left[(S_T - K)^+ \,|S_0\right] = S_0^2\, F_R(\mu, \sigma, T), \\
\mathrm{Var}_{L,j}(v_T) &= \mathrm{Var}\left[(S_T - K)^+ \,|S_{L,j}\right] = \widehat{S}_{0,j}^2 F_L(\mu, \sigma, T),
\end{aligned} \tag{5}$$

where expressions for $\theta_R(\cdot)$, $\theta_L(\cdot)$, $F_R(\cdot)$, and $F_L(\cdot)$ are provided in the appendix. Accordingly, the two types of agents' demands are given by:

$$\begin{aligned}
y_R(P_0) &= \frac{S_0\, \theta_R(\mu, \sigma, T) - P_0}{\alpha_R S_0^2\, F_R(\mu, \sigma, T)}, \\
y_{L,j}(P_0) &= \frac{\widehat{S}_{0,j} \theta_L(\mu, \sigma, T) - P_0}{\alpha_L \widehat{S}_{0,j}^2 F_L(\mu, \sigma, T)}.
\end{aligned} \tag{6}$$

1.3 Market makers

The market makers (dealers) execute the orders at $t = 0^+$ and hedge in the time interval $t \in (0^+; T)$ to reduce the risk of their positions. If there are no hedging costs and the MMs can hedge perfectly, their positions are risk free, and they price the asset according to the standard Black-Scholes model. In this case, any non-zero mispricing would be immediately eliminated by the MMs. However, as GPP (2009) point out, in the presence of hedging costs, the MMs cannot hedge perfectly, and their positions are not completely risk free. This implies that the demand pressure from end users affects the price of the option.

To keep the model analytically tractable, we assume that the hedging costs are small, so that MM's replication strategies are close to the standard delta-hedging rules in the Black-Scholes framework. In other words, following GPP (2009), we ignore the feedback effect of the imperfect hedging on the hedging strategies and the underlying stock price. Also following GPP, we assume that MM have mean-variance utility.

In contrast to GPP (2009), we explicitly take into account the discreteness of hedging strategies as a natural consequence of the hedging costs faced by the market makers. We assume that trading costs are exogenously given, while the optimal number of trades arises endogenously in the model.

To construct their hedge portfolios, MMs take positions both in the option and underlying stock. Their portfolio value at time t is $\Pi_t = \theta_C v_t + \theta_{S,t} S_t$, where θ_C and $\theta_{S,t}$ are the numbers of call options and shares of the stock invested at time t, and v_t and S_t are the call price and the stock price at time t. Note that the number of options in their portfolios θ_C is constant over time and they hedge by adjusting their positions in the underlying stock price $\theta_{S,t}$. Taking into account that the strategies are self-financing, we have $d\Pi_t = \theta_C dv_t + \theta_{S,t} dS_t$. The hedging strategies are given by $\theta_{S,t} = -\theta_C \partial v_t / \partial S_t$.

The MMs cannot hedge continuously due to the transaction costs, and therefore their number of trades N in the interval $t \in (0, T)$ is finite but large (because we assume low hedging costs). As we show in Appendix A, this assumption ensures the tractability of the model. It follows that the interval Δt between the subsequent trades, $\Delta t = T/N$ is small. Define the value of the portfolio per unit of option as $\pi_t = \Pi_t / \theta_C = v_t - S_t \partial v_t / \partial S_t$. Similar to GPP (2009), we obtain that the increment of π_t over a short but finite time interval Δt is given by

$$\begin{aligned} \Delta \pi_t &= \frac{1}{2} S_t^2 \sigma^2 \frac{\partial^2 v_t}{\partial S_t^2} \left(\Delta Z_t^2 - \Delta t \right) + o(\Delta t) \\ &= \frac{1}{\sqrt{2}} S_t^2 \sigma^2 \Gamma_t \Delta t \eta_t + o(\Delta t) \end{aligned} \tag{7}$$

where Z_t is the Brownian motion driving the stock price process, and Γ_t is the gamma of the option at time t. As in GPP (2009), Γ_t in equation (7) is the Black-Scholes gamma because, as we discuss above, we ignore the feedback effect of imperfect hedging on the hedging strategies. We have used the fact that $\Delta Z_t^2 - \Delta t = \sqrt{2} \Delta t \eta_t$ in the second line of the above equation with $\mathrm{E}[\eta_t] = 0$ and $\mathrm{E}[\eta_t^2] = 1$ being i.i.d. and uncorrelated for different time intervals t.[6] Since hedging is not perfect, the MMs' portfolio π_t has a risky component characterized by the finite residual volatility. The variance of MMs' terminal portfolio per

[6]The variable η_t is a demeaned squared standard Normal with a pdf $\rho(\eta_t) = \frac{1}{\sqrt{2\pi}} \frac{\sqrt{2}}{\sqrt{1+\sqrt{2}\eta_t}} \exp\left(-\frac{1+\sqrt{2}\eta_t}{2} \right)$. It is straightforward to see that $\mathrm{E}[\eta] = 0$ and $\mathrm{E}\left[\eta^2\right] = 1$.

unit of option, π_T, is shown in Appendix A to be given by:

$$\mathrm{Var}_M(\pi_T) = S_0^2 \Phi(\sigma^2 T/4)/N = \Sigma_M/N, \tag{8}$$

where the function $\Phi(\cdot)$ is defined in the Appendix A and $\Sigma_M \equiv S_0^2\Phi(\sigma^2 T/4)$. It follows that the variance of the MMs position is small and proportional to $1/N$. Recall that in the absence of hedging costs, $N \to \infty$, the hedging is perfect, the MMs position is risk free, and $\mathrm{Var}_M(\pi_T) \to 0$. Also, note that for finite but small hedging costs, $\mathrm{Var}_M(\pi_T)$ is proportional to S_0^2.

1.3.1 MMs' optimization

The problem of the market makers is more complex than that of the R and LA agents, since, as we discuss above, in addition to optimizing their option positions they also must choose the optimal number of hedging trades N in the interval $(0,\, T)$. For analytical tractability, we assume that the hedging cost is quadratic in the quantity of options q for each trade, and hence the total cost of all trades is $h = \chi q^2 N$ with $\chi > 0$. We further assume that like the R and LA agents, MMs also maximize mean-variance utility. When hedging costs are zero, the value of the MM's hedge portfolio is equal to the Black-Scholes price of the option v_0 times the number of options q and hence the total value of their portfolio is $q(P_0 - v_0)$, where P_0 is the equilibrium price of the option. With hedging costs, the mean and the variance of the MMs payoff at the maturity of the option T are given by:

$$\begin{aligned} \mathrm{E}_M(v_T) &= q(P_0 - v_0) - \chi q^2 N \\ \mathrm{Var}_M(v_T) &= q^2 \frac{\Sigma_M}{N}, \end{aligned}$$

where Σ_M is given by (8). In this case the MM's expected utility is given by:

$$\mathrm{U}(q, N) = q(P_0 - v_0) - \frac{1}{2}\alpha_M q^2 \frac{\Sigma_M}{N} - \chi q^2 N. \tag{9}$$

Optimization w.r.t. N yields the optimal number of hedging trades $N^* = \sqrt{\alpha_M \Sigma_M / 2\chi}$. Note that $N^* \to \infty$ as the hedging cost $\chi \to 0$, as expected. Substituting back into the expected utilty, we obtain a quadratic optimization problem w.r.t. the quantity q:

$$\mathrm{U}^*(q) = q(P_0 - v_0) - \sqrt{2\chi\alpha_M\Sigma_M}\, q^2. \tag{10}$$

Optimizing w.r.t. q, we obtain the MMs supply:

$$y_M(P_0) = \frac{P_0 - v_0}{\sqrt{8\chi\alpha_M\Sigma_M}} = \frac{P_0 - v_0}{S_0\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}} = \frac{P_0 - S_0\theta_0}{S_0\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}}. \tag{11}$$

Note that the demands of the rational agent, $y_R(P_0)$, and of the limited-attention agent, $y_L(P_0)$ are proportional to S_0^{-2} while the supply from the market maker, $y_M(P_0)$ is proportional to S_0^{-1}. This is a natural consequence of hedging with endogenous number of trades N^* which itself increases in S_0.

1.4 Equilibrium

Combining equations (6) and (11) and applying the market clearing condition $N_R y_R(P_0) + \sum_{j=1}^{N_L} y_{L,j}(P_0) = N_M y_M(P_0)$, gives the equilibrium price. We derive this equilibrium price in equation (A12) in the Appendix. The expression for the equilibrium price is simplified significantly if the drift of the stock price is low, $(\mu - r_f)/\sigma^2 \ll 1$.[7] Under these conditions, we obtain the following result:

Proposition 1: *In the limit of a small drift,* $\mu \simeq 0$ *, of the stock, mispricing is given by:*

$$\frac{P_0 - v_0}{v_0} = \frac{\eta\left(\overline{S}/S_0\right)^{1-k} - 1}{1 + A\left(\overline{S}/S_0\right)^{2(1-k)} + B\left(\overline{S}/S_0\right)^{1-2k}}, \tag{12}$$

where expressions for η*,* A*, and* B *are provided in the Appendix and* k *is defined in equation* (1).

The functional form of mispricing, given by equation (12), leads to the following predictions:

H1: Options on "low-priced" stocks with $S_0 < \overline{S}\eta^{\frac{1}{1-k}}$ are *overpriced*, $P_0 - v_0 > 0$, and options on "high-priced" stocks with $S_0 > \overline{S}\eta^{\frac{1}{1-k}}$ are *underpriced*, $P_0 - v_0 < 0$. As follows from (1), the LA investors' estimates of the stock price are biased upwards for low-priced stocks and biased downwards for stocks with high prices. The assumed lognormality of the prior distribution as well the LA's private signal introduce additional factor into misprising, represented by the parameter η.

H2: This effect is asymmetric in the underlying stock price S_0 and the magnitude of mispricing is higher for stocks with low S_0. First, the numerator in equation (12) is non-linear

[7]Note that while this restriction on the drift significantly simplifies the analysis, our results also hold in the general case when this restriction is not satisfied.

in the underlying price. For example, when $\eta = 1$ and $k = 0$ (which corresponds to a complete lack of attention of the LA agents) the mispricing is bounded below by -1 for high price stocks but is unbounded above for low price stocks. In addition, the denominator in equation (12) is non-linear in $x = \left(\overline{S}/S_0\right)^{1-k}$. It can be shown that for $k > 0.5$ (which corresponds to the case of relatively low inattention, as is likely the case in the real world), the denominator increases in the underlying price S_0, therefore contributing to the asymmetry in mispricing.

H3: The mispricing is *increasing* in the relative number of LA agents, *decreasing* in their risk aversion parameter α_L, and *increasing* in the noisiness of their signal σ_ϵ (which can be interpreted as a proxy for inattention). The relative number of LA agents as well as their degree of inattention, as proxied by σ_ϵ, can be interpreted as the general level of inattention in the market. Since the demand of LA agents is inversely proportional to their risk aversion, higher degree of risk aversion limits their demand and attenuates the resulting mispricing.

H4: The mispricing *decreases* when the hedging costs χ decrease and when the number of market makers N_M increases. Low hedging costs reduce the resulting variance of the MM's payoff, therefore increasing their supply and reducing mispricing. A higher relative number of market makers also increases their supply and drives mispricing down.

We use these model predictions to guide our empirical analysis in the rest of the paper.

2 Option returns and the underlying price

2.1 Data and variables

Our primary source of data is Ivy DB OptionMetrics which provides comprehensive coverage of U.S. equity options from 1996 through 2017. OptionMetrics provides daily closing bid-ask quotes (as well as daily trading volume and open interest) on standard American options. Following standard practice (see, for example, Cao et al. (2017)) we impose many filters on the option data. We remove options with zero open interest and options with zero trading volume, because such options are illiquid, and their quotes are less likely to reflect any useful information. We eliminate observations that violate arbitrage bounds, for which the ask price is lower than the bid price, or for which the bid price is equal to zero. We retain only options maturing on the third Friday of a month.

For each underlying security in each month, we pick a single call option and a single put option closest to ATM, within moneyness (ratio of stock price to strike price) boundaries of 0.7 and 1.3. We merge the option data with underlying equity data obtained from the CRSP dataset, using the matching algorithm provided by OptionMetrics. The resulting sample includes 257,107 call options and 204,123 put options. Following the predictions in Section 1.4, to gauge the effect of the underlying price on option prices, each month we sort all options into ten equal-sized deciles based on the market price of the underlying stock.

Table 1 presents summary statistics for our sample. We report statistics for characteristics of the options and their underlying stocks for the full sample as well as for decile one (low stock price) and decile ten (high stock price). For each variable, we first calculate the cross-sectional mean and median across stocks. We then report the time-series averages of these means and medians. To reduce the influence of outliers in our tests, we winsorize all variables at the 1st and the 99th percentiles.

Existing studies (see, for example, Cao and Han (2013), Cao et al. (2017), and Goyal and Saretto (2009)) have identified multiple stock and option characteristics that affect option returns. Following these studies, the first set of characteristics is related to underlying stocks. Size is the equity value of the underlying stock (in millions of dollars). Market-to-book is the ratio of current equity market value to equity book value as of previous quarter. Past return of the underlying stock is cumulative return over the past six months. Profitability is the annual income before extraordinary items divided by the previous year's book equity value. Analyst forecast dispersion is the ratio of the standard deviation of analyst earnings forecast to the absolute value of the consensus mean forecast; for each firm-month we use the average dispersion over the previous three months. Net shares issuance is measured by the annual log change in split-adjusted shares outstanding. Illiquidity of the underlying stock is the Amihud's (2002) measure, calculated by the monthly average of daily ratios of absolute return to dollar trading volume (in millions). IVOL, ISKEW, and IKURT are the standard deviation, skewness, and kutrtosis of the residuals from regressions of daily stock returns on the Fama and French (1993) three factors in the past three months. MAX10 is the average of the highest 10 daily returns during that period. Byun and Kim (2016) use ISKEW and MAX10 to proxy for lottery characteristics of stocks.

The remaining variables in Table 1 relate to options themselves. Volume/open interest is the ratio of daily option trading volume of a given option contract to total open interest for the same contract (as of the end of the trading day). This is a measure of liquidity of a given option contract. The second option liquidity measure that we use is the bid-ask spread, computed as the difference between the ask and bid quotes at the closing scaled by the midpoint quote. IV−HV is the difference between the option's implied volatility (IV) and historical volatility (HV). IVs are provided by OptionMetrics. We compute HVs based on daily returns over the past year. Gamma is the second derivative of the option price with respect to the stock price, and vega is the derivative of the option price with respect to volatility.

By construction, there is a big spread in underlying prices across the decile portfolios–from an average of $7.31 in decile one to $141.66 in decile ten. Not surprisingly, decile one options (both put and calls) have lower prices than decile ten options. Stocks in the first decile also have lower market capitalization, lower market-to-book ratios, lower past returns, and are less profitable than stocks in the tenth decile. Decile one stocks also tend to have higher idiosyncratic volatility and more positively skewed returns than decile ten stocks.

Option characteristics also differ across deciles. Both puts and calls in decile one have higher gammas, lower vegas, and higher IVs than those in decile ten. Interestingly, options in decile one have higher IV−HV, suggesting potential overpricing of those options relative to those in decile ten. The large differences in both stock and option characteristics across the extreme deciles makes it important to control for those characteristics in our tests. We do so via double sorts and FM regressions presented later in this section.

2.2 Delta-hedged option portfolio returns

To test our main hypothesis H1, We start our analysis by constructing delta-hedged call and put portfolios sorted on the underlying price, as suggested by our model in Section 1.[8] We hold the delta-hedged portfolios until the maturity of the options. We closely follow Cao and Han (2013) and Goyal and Saretto (2009) to calculate option returns. The return is equal to the total dollar gain at expiration scaled by the absolute value of the total cost of constructing portfolios at the formation date. Thus, for delta-hedged calls we scale by $|C_0 - \Delta_{C,0} S_0|$ while for delta-hedged puts the scaling factor equals $P_0 - \Delta_{P,0} S_0$ (note that the delta of a put option is negative), where S_0, C_0, and P_0 are the stock, call, and put option prices at the initiation of the position and $\Delta_{\cdot,0}$ are deltas at the initiation of the position. We compute option returns from quote midpoints and use option deltas provided by OptionMetrics. We explore trading at additional points in the bid-ask range to examine the effect of transaction costs on our results in Section 2.7. We explore alternative rebalancing and holding periods

[8] Going beyond Section 1's model, it is important for us to sort on the underlying stock price and not on option price itself. Option prices may be low because investors' other biases drive these prices to be low. For example, Goyal and Saretto (2008) find that options with low implied volatility (low prices) are too cheap perhaps because of investors' mis-estimation of future volatility. Thus, low option price would conflate the effect that we are trying to uncover. When we sort on the underlying stock price we are not subject to this problem as there is no a priori reason to believe that options written on stocks with low prices have low IVs. In unreported results, we do find that our portfolio sort results are weaker for sorts on option prices.

in the Internet Appendix Section IA.1.

Table 2 shows returns to equal-weighted decile portfolios sorted on the underlying stock price (as in Table 1). We report mean excess returns (in excess of the risk-free rate) as well as alphas from a factor model. Our factor model includes both stock-based and an option-based return factor. The stock factors are the Fama and French (2015) five factors and the momentum factor. The option factor is the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. These option factors are also used in Cao and Han (2013) and Cao et al. (2017). We match the holding period of option returns to that for factors. Since some months have four weeks between expirations and some five, we convert all returns to weekly returns (by simply dividing the return by the number of weeks in the holding period). We then report all returns and alphas in percent per week. The $10-1$ portfolio is constructed as long in decile ten (long option and short Δ shares) and short in decile one (short option and long Δ shares). For robustness, we also show value-weighed (opt-vw) returns and alphas of the $10-1$ portfolio, where value weighting is done according to the market value of the options' open interest.

Table 2 shows that most of the portfolio returns as well as alphas from the 7-factor model are negative. This is consistent with the findings of Bakshi and Kapadia (2003), Cao and Han (2013), and Goyal and Saretto (2009). For our purposes, we find that, for delta-hedged call and put portfolios, returns as well as alphas generally increase (albeit not monotonically) from decile one (low underlying price) to decile ten (high underlying price). For example, average excess return of delta-hedged calls in decile one portfolio (lowest underlying prices) is -0.68% per week, while the return on decile ten portfolio (highest underlying price) is -0.14% per week. The corresponding 7-factor alphas are -0.55% per week for decile one and -0.06% for decile ten. Returns and alphas on the delta-hedged put portfolios exhibit a similar relationship with the underlying price. For example, for delta-hedged puts mean excess returns on decile one portfolio (lowest underlying prices) is -0.46% per week, while the return on decile ten portfolio (highest underlying price) is -0.12% per week.

These results are in accord with prediction H1, that options on low-priced stocks are too expensive, in Section 1.4. Prediction H2 says that the effect on option price is asymmetric in the underlying price and the magnitude of overpricing is higher for options on lower-priced stocks than the magnitude of underpricing for options on higher-priced stocks. These implications are broadly borne out by results in Table 2. The returns/alphas exhibit non-linear patterns across the stock price deciles, indicating a greater mispricing for decile one than for decile ten. For example, for delta-hedged calls, the absolute difference between the alphas of decile ten and deciles five/six is around 0.10%, whereas the difference between the alphas of deciles five/six and decile one is around 0.40%. Similarly, the equivalent gaps in alphas for delta-hedged puts are around 0.07% and 0.24%.

The returns and alphas of the long-short 10−1 portfolio are positive and strongly statistically significant. For example, the weekly average return and the 7-factor alpha for delta-hedged calls is 0.54% and 0.50%, respectively. In annualized terms, our strategy generates 10−1 portfolio 7-factor alphas of 26.00% and 16.64% for delta-hedged calls and puts, respectively. The last column of Table 2 shows that the results are also robust to the alternative weighting scheme whereby options are weighed by the market price of the options' open interest.

Option returns are non-linear functions of underlying stock return over discrete intervals. In principle, delta-hedged option returns are invariant to underlying return only for continuously adjusted deltas (and then only if the pricing model used to compute deltas adequately describes the stock dynamics). Therefore, the use of linear factor models may not be appropriate to calculate risk-adjusted returns. To alleviate this concern, we also do conditional beta tests similar to those in Goyal and Saretto (2008). Specifically, we run the following time-series regression:

$$R_{pt} = \alpha_p + \left(\beta_{0p} + \beta'_{1p}\Theta_{pt-1}\right)' F_t + e_{pt}, \tag{13}$$

where Θ_p are option Greeks (delta, gamma, and vega) calculated as averages of individual options for each decile. Unreported results show that the alphas from these conditional beta models are even higher than those in Table 2. For example, the 7-factor alphas for the 10−1 portfolio of delta-hedged calls and puts are 0.55% and 0.36%, respectively (versus the base case scenario of 0.44% and 0.29%, respectively).

One potential concern about Table 2 results is that the underlying price might be correlated with some other stock or option characteristics. These characteristics are left unmodeled in our theoretical analysis in Section 1 but are known to affect future option returns. For example, as shown in Table 1, stocks with low prices tend to have higher idiosyncratic volatility, lower market capitalization, lower market-to-book ratios, and lower past returns. We already partly control for the potential effect of these additional variables by reporting alphas from factor models in addition to raw excess returns. To further alleviate this concern, we perform two different types of tests. First, we double sort our option portfolios on various stock characteristics and on the underlying stock price. We then check if within each characteristic-sorted portfolio the underlying price has explanatory power for future option returns. Second, we run FM regressions of option returns on the underlying stock price while controlling for various stock and option characteristics.

2.3 Double-sorted portfolios

To account for potential correlation of the underlying stock price with various stock characteristics, we examine returns to double-sorted portfolios. Each month, we first sort all options into quintiles based on a stock characteristic from Table 1. These characteristics include size, market-to-book ratio, past stock return, profitability, analyst forecast dispersion, and net equity issuance. All these characteristics have been shown by Cao et al. (2017) to have predictive power for future option returns. To account for skeweness preferences, we also include three variables that proxy for skewness, viz. IVOL, ISKEW, and MAX10. Byun and Kim (2016) also use ISKEW and MAX10 to proxy for lottery characteristics of stocks.

We sort the options further into deciles according to the market price of the underlying stock. This procedure results in fifty characteristic/stock price portfolios. For each stock price decile, we average returns across the characteristic quintiles, yielding ten stock price decile returns. We then compute the difference between decile ten (highest underlying price) and decile one (lowest underlying price). This procedure controls for correlation between the underlying stock price and various stock characteristics. For example, if the effect of the underlying price on delta-hedged option returns is driven primarily by price's correlation with size, then returns to long-short portfolios in this analysis should be indistinguishable from zero because our portfolios are first sorted on size.

Table 3 reports the 7-factor alphas of the 10−1 portfolio. The alphas reported in Table 3 are generally lower than those in Table 2, ranging between 0.17% per week (puts) for stock illiquidity control to 0.41% per week (calls) for past stock returns control. This suggests that portfolio returns in Table 2 can indeed be partly attributed to the fact that some of the stock characteristics known to predict option returns are correlated with the underlying price. For example, size is clearly positively correlated with the stock price and has been found to positively affect option returns (Cao et al. (2017)). Accordingly, we find that alphas from size control are roughly half (0.26% for calls and 0.19% for puts) of those in the baseline results. Market-to-book and past stock return controls have less of an effect on option returns.

Importantly for us, the effect of the underlying stock price remains highly significant for all stock characteristics when performing the double sort. Table 3 shows that the t-statistics on the averaged long-short portfolios range between 5.08 and 8.28 for delta-hedged calls and between 4.07 and 7.32 for delta-hedged puts. We conclude that the effect of the underlying stock price on returns to delta-hedged call and put portfolios is robust to the double-sorting procedure.

2.4 Fama-MacBeth regressions

In order to explicitly control for other determinants of the cross-sectional patterns in option returns, we perform a multivariate regression analysis by running FM regressions. An additional advantage of this approach is that it allows us to gauge the marginal influence of the underlying stock price on delta-hedged option returns. The dependent variable is the delta-hedged call or put return. Our explanatory variable of interest is the logarithm of the underlying stock price. According to our main inattention hypothesis, options are overpriced on low-priced stocks, and therefore, we expect a positive coefficient on this variable.

We present the estimation results in Table 4. We include skewness related characteristics (IVOL, ISKEW, IKURT, and MAX10) and other option and stock characteristics as controls. The option characteristics include measures of option liquidity such as the ratio of option volume to open interest and option bid-ask spread, and also option greeks such as gamma (the second derivative of the option price to the underlying price) and vega (the sensitivity of the option price to stock return volatility) that can potentially reflect difference in the riskiness of options and, therefore, affect option returns. We also include IV$-$HV following Goyal and Saretto (2009) who document that this variable is a strong predictor in the cross-section of option returns. The stock characteristics include logarithm of market capitalization, logarithm of the market-to-book ratio, past six month stock return, profitability, analyst forecast dispersion, net equity issuance, and Amihud's (2002) illiquidity measure. The effects of most of these characteristics on option returns have been examined in Cao et al. (2017).

Regression coefficients reported in Table 4 on the various stock and option characteristics are generally consistent with the existing studies. While the ratio of option volume to open interest does not affect subsequent option returns, the bid-ask spread has a significant negative effect for both put and call returns, while option bid-ask spread has a negative effect for the delta-hedged portfolios. This is consistent with the idea that investors in options markets demand additional compensation for holding illiquid option positions if they have net short option positions. Note that Lakonishok, Lee, Pearson, and Poteshman (2006) find that non-market maker investors in aggregate have more written than purchased options. Consistent with the findings of Goyal and Saretto (2009), IV$-$HV is negatively related to option returns for the delta-hedged call and put portfolios. Options' gamma has a significant positive effect while vega has a significant negative effect confirming the importance of controlling for specific aspects of the riskiness of option portfolios.

Size has a significant negative effect on portfolio returns, again indicating the importance of controlling for stock characteristics in our regressions (as size is clearly positively correlated with the stock price). The effect of the market-to-book ratio is negative albeit statistically insignificant. Amihud's (2002) measure of stock illiquidity is negative and highly significant in our regressions of option returns.

The coefficient on the logarithm of the underlying stock price, our main variable of interest, remains positive and highly statistically significant after including both stock and option characteristics as controls. The coefficient is 0.745 (t-statistic = 7.51) for calls and 0.587 (t-statistic = 7.19) for puts. This effect is also economically large. For example, the coefficient estimates imply that the returns to delta hedged call portfolios increase by 0.52% per week when the underlying stock price moves by one standard deviation.[9]

We provide many additional robustness tests in the Internet Appendix IA.1. These include empirical choices for computing option returns (return to month-end, return to next week, daily rebalancing), trading in-the-money (ITM) options, OTM options, and options with time to maturity of more than one month; and various sub-sample splits.

2.5 Alternative measure of mispricing

We have identified mispricing by analyzing post-formation returns. While this is the standard approach for stock returns, one benefit of analyzing options is that there are rigorous theoretical option pricing models that derive option prices as functions of several inputs. Therefore, one can alternatively look at the deviation of the actual option price from that given by an established option pricing model. The advantage of this approach is that it focuses directly on mispricing and is not subject to the extreme nature of option returns (Broadie, Chernov, and Johannes (2009)). If the assumptions of the option-pricing model are fully met, then this approach would result in the cleanest measure of mispricing. This approach is also more consistent with our model in Section 1.4 which makes predictions about option 'prices.' The downside, of course, is that the option pricing model is unlikely to be the true model. Remaining cognizant of these limitations, we use an alternative measure only as a proxy for mispricing when examining the relationship between mispricing and the stock price. In particular, we use the Black-Scholes model, the most established and widely used in the options literature, as the benchmark model for theoretical option prices.

[9]We use options that are closest to ATM from a sample of options with moneyness between 0.7 and 1.3, and as such, permit the entry of OTM or ITM options in some cases. The evidence on the volatility smile indicates that OTM and ITM options tend to be more expensive (from an implied-volatility perspective) than ATM options. To check for this potentially confounding effect, we include moneyness or its absolute value as an additional control in FM regressions. We find that this does not materially change the coefficient of interest. For example, in regressions of delta-hedged calls, the coefficient on log stock price declines from 0.745 to 0.743 (0.716) with moneyness (absolute moneyness) as an additional control.

We calculate Black-Scholes prices based on both historical volatility of the underlying stock return and the conditional expected volatility derived from a GARCH(1,1) model applied to monthly returns. The latter volatility measure captures expected future changes in volatility. Note that the difference between the Black-Scholes price and the actual option prices is correlated with IV−HV. Nevertheless, the difference in prices provides a more accurate proxy for mispricing than IV−HV as Black-Scholes prices are not linear in volatility and depend on various additional inputs. We measure the extent of mispricing by the log of the ratio of the theoretical Black-Scholes price to the actual option price. A relatively high measure indicates potential underpricing of the option while a relatively low measure indicates potential overpricing. We reiterate that we do not claim that the Black-Scholes option price is the correct price. Rather, we use the deviations from the Black-Scholes price just as a proxy for mispricing.

Table 5 shows the results from FM regressions with log of the theoretical/actual option value ratio as the dependent variable. The controls are the same as in Table 4 except that we do not include IV−HV as discussed above. The variable of interest is the logarithm of the stock price. Based on our hypothesis, we expect a positive coefficient; more underpricing (overpricing) on high- (low-) priced stocks. Our results confirm this hypothesis. The coefficient estimates for both calls and puts are positive and strongly statistically significant. Although the coefficient estimates change, the results are also consistent across our use of historical volatility and GARCH volatility to price options.

Thus, the results from this alternative model-based misvaluation measure complement and reinforce our evidence based on portfolio returns and demonstrate a robust positive relation between potential mispricing and the underlying stock price. To summarize, the cross-sectional regressions in Tables 4 and 5 coupled with portfolio results in Tables 2 and 3 demonstrate a robust and significant effect of the underlying stock price on option returns. This evidence supports our main hypothesis H1 from Section 1.4 that options on low-priced stocks are overpriced.

2.6 Is it skewness preference?

Literature documents that investors have preference for low-priced assets because of skewness preference (Barberis and Huang (2008) and Mitton and Vorkink (2007)) or lottery preferences (Bali, Cakici, and Whitelaw (2011) and Kumar (2009)). Our sorting variable is the underlying stock price and not the option price. Therefore, our results do not speak directly to the nominal-price puzzle literature. Nevertheless, preference for lottery-like stocks might also translate into preference for options on such stocks (Blau, Bowles, and Whitby (2016) and Byun and Kim (2016)). Could skewness preference explain our option results? We test for skewness preference in options in three different ways.

First, Table 3 shows that the effect of underlying price on delta-hedged option returns is robust to the inclusion of ISKEW and MAX10, the two variables used in Byun and Kim (2016) to proxy for lottery characteristics. We also experiment with independent sorts based on ISKEW/MAX10 and the underlying price. In unreported results, we find that the 7-factor alphas of long-short portfolios that are long in decile ten (highest underlying price) and short in decile one (lowest underlying price) for each of the characteristic quintile are positive and statistically significant in a vast majority of cases (37 out of 40).

Second, we explicitly control for skewness characteristics of underlying stocks in FM regressions as shown in Table 4. We find that the coefficient on the logarithm of the underlying stock price, our main variable of interest, remains negative and highly statistically significant even after including these additional controls.

Third, we directly calculate the skewness of our option portfolios. Note first that the descriptive statistics in Table 1 show that decile one stocks do have higher (physical) skewness than decile ten stocks. What is more relevant for us is skewness of option returns. We calculate realized option return skewness in two different ways. First, we calculate the skewness from the time-series of option portfolio returns. Second, following Boyer and Vorkink (2014), we calculate cross-sectional skewness. For the latter, we first calculate skewness from the cross-section of option returns in portfolio each month. We then take the time-series average of these skewness measures.

We do all these calculations for delta-hedged returns separately for calls and puts and report the results in Table 6. We find that, on average, the skewness increases as one goes from decile one to decile ten (the pattern is not always monotonic). For instance, portfolio skewness of delta-hedged call returns for deciles one and ten is 1.679 and 3.425, respectively. Skewness calculated from the cross-section of individual option returns shows the same patterns as the decile one and ten skewness are 0.988 and 1.754, respectively.

It may seem puzzling to contrast our results with those of Boyer and Vorkink (2014) who find that realized option returns are negatively related to their expected skewness. One difference between their study and our results is that we use realized skewness while Boyer and Vorkink use expected skewness. The calculation of expected skewness necessitates calculation of expected return on stock, an admittedly difficult task. Our use of realized skewness avoids this problem. Second, Boyer and Vorkink analyze raw option returns while we study delta-hedged option returns to strip away the effect of underlying stock returns. Third, and perhaps most important, Boyer and Vorkink sort options based on their measure of expected skewness where our sorting variable of price does not produce the same spread in skewness. Thus, our results are not necessarily inconsistent with those of Boyer and Vorkink.

Finally, we note that investors seeking to enhance the skewness of their portfolios are likely to be attracted to calls and not puts. Indeed, buying a call on a stock that offers positively skewed returns would result in an even higher skewness. By contrast, put returns are negatively correlated with the underlying stock returns and long puts generate positive payoffs when the underlying stock returns are negative. Thus, buying puts on stocks with positively skewed returns is akin to buying calls on stocks with negatively skewed returns and, thus, is not a viable strategy for a skewness-seeking investor. However, we document strong results for both calls and puts, inconsistent with the skewness preference hypothesis.

2.7 Transaction costs

Our results so far rely on calculating option returns from midpoint bid-ask quotes. The actual trading prices might be different and, therefore, influence our results. Prior literature shows that transaction costs in option markets are high (see, for example Figlewski (1989), George and Longstaff (1993), and Ofek, Richardson, and Whitelaw (2004)). We consider various scenarios of trading at prices that differ from midpoint quotes. In particular, we consider trading at various values of the effective bid-ask spread (ESPR) measured in percentage of the quoted bid-ask spread (QSPR). For example, if the bid price of an option is \$3 and the ask price is \$4, then, assuming ESPR/QSPR = 50%, we buy the option at \$3.75 (for the long leg of the 10−1 portfolio) and sell the option at \$3.25 (for the short leg of the 10−1 portfolio). The effective bid-ask spread of zero then corresponds to our main results reported in Table 2. Recall that we keep the options until expiration and, therefore, these adjustments apply only to prices at the initiation of positions.

The descriptive statistics in Table 1 show that mean bid-ask spread is 0.348% (0.118%) for call options in decile one (ten). Therefore, we expect the transaction costs to have a substantial impact on options in decile one but an inconsequential impact on options in decile ten. We report both the mean excess returns as well as the 7-factor alphas from these tests in Table 7. These returns and alphas are reported for the top decile ten (high stock price), the bottom decile one (low stock price), as well as for the 10−1 portfolio.

As expected, the returns and alphas to the short (decile one) portfolio increase, and become less negative, as ESPR increases (when we sell at a lower price), while returns to the long (decile ten) portfolio decrease. The effects are more pronounced for decile one than for decile ten. For example, return to delta-hedged calls decrease (in absolute value) from −0.68% for zero spread to only −0.35% for ESPR/QSPR = 50%. Similarly, return to delta-hedged puts decrease (in absolute value) from -0.46% for zero spread to only -0.22% for ESPR/QSPR = 50%. The mean excess returns of the 10−1 portfolio remain highly statistically significant for the values of ESPR less than 25% of QSPR for both delta-hedged calls and puts. However, for trades at prices beyond this range, for example at ESPR/QSPR = 50%, the transaction costs prevent the profitable execution of our strategy for puts as the mean returns of 10−1 puts portfolio are only 0.06% (t-statistic = 1.38) for puts. At these high level of transaction costs, call 10−1 portfolio average returns, while small at 0.17%, remain statistically significantly different from zero.

The effect of transaction costs is similar for 7-factor alphas. The alphas are positive and statistically significant for ESPR up to 25% of QSPR for both delta-hedged calls and puts, and for delta-hedged calls for ESPR/QSPR = 50%. However, they are economically small (and statistically insignificantly different from zero) for puts for ESPR/QSPR = 50% (they remain statistically significant for ESPR/QSPR = 40%; results not reported). Note that in actual practice, option traders would have the whole day to decide when to optimally trade and minimize the market impact costs. For example, Muravyev and Pearson (2020) argue that, once one takes trade timing into account, effective spreads are much lower than the usually measured spreads. They estimate that effective spreads are only 30% of the quoted spread for such timers, albeit for a sample of S&P 500 stocks. At these levels of spreads, post-transaction-cost returns and 7-factor alphas of the D10−D1 portfolio are significant for both delta-hedged calls and puts.

3 Quasi-natural experiments

3.1 Stock splits

Stock splits provide a natural laboratory to study the effect of the underlying stock price on the prices of options and their potential misvaluation. Many studies show that stock attractiveness increases following splits (see, for example, Easley, O'Hara, and Saar (2001) and Schultz (2000)). Stock splits may act as a signaling device by which the management conveys information to outside investors about the fundamental prospects of the company. For example, Lakonishok and Lev (1987) find mean reversion in earnings growth around stock splits, although Weld, Michaely, Thaler, and Benartzi (2009) question the signaling aspect of splits. There is also some evidence of abnormal stock returns following splits (see, for example, Desai and Jain (1997)). Thus, it may be that the post-split stock price is not the same multiple of the pre-split stock price as the split ratio.

We design a test statistic that is agnostic about the information content, if any, of stock splits. We posit that, absent any behavioral biases of the kind modeled in Section 1, the ratio of the price of an ATM option (either a put or a call) to the price of the stock should not change around the split. On the contrary, if (limited-attention) investors do not pay attention to the underlying price, then post-split options (on lower-priced stocks) should be overpriced relative to pre-split options (on higher-priced stocks). This implies that the ratio of option-to-stock price should increase following the split. Since we analyze the pre- and post-split ratio of option to stock price, our hypothesis is immune to the information effects on the underlying stock.

To test this hypothesis, we collect a sample of stock splits from CRSP. Our sample contains 1,914 stock splits (with split ratio of two or more) with traded options over the 1996 to 2017 sample period. For each stock split, we first identify the shortest maturity options among all options with at least one-month to maturity, and then pick the option that is closest to ATM. Panel A of Table 8 shows the summary statistics of the stock split sample. In most cases the split ratio was two, though the distribution of the split ratio is highly skewed with the maximum ratio of 50.[10] The average pre-split stock price is $94.95 which goes down to $42.97 post-split.

To formally test the hypothesis of investors' behavioral reaction to the underlying stock price, we examine the change to the option/stock price ratio around the stock split. The main variable of interest is defined as:

$$\text{Post/Pre-split option/stock ratio} = \frac{\text{Post-split option price/ Pre-split option price}}{\text{Post-split stock price/Pre-split stock price}} \tag{14}$$

for calls and puts separately. We analyze windows of one, three, and five days before and after the stock split day. The null hypothesis is that this price ratio equals one. If investor inattention results in overpricing of option on low-priced stocks, then the price ratio should be greater than one as option prices react to the split and the consequent change in the underlying stock prices.

Panel B of Table 8 presents the results from the t-test for the null hypothesis that the post/pre-split option/stock ratio is equal to one. We find that the change in the option-to-stock price ratio is always greater than one, across all the time windows and for both puts and calls. For example, call options become 14% more expensive relative to the underlying price within a five-day window around a stock split, while put options become 16% more expensive over the same window.

[10]When we restrict the sample to include only 2-for-1 splits, there is almost no change in our results.

If the split has (on average) an effect on the valuation of the stock (Desai and Jain (1997)), then this will change the moneyness of the option in a systematic way. Since OTM and ITM options tend to be more expensive than ATM options (the volatility smile), this could potential impact the results in Panel B of Table 8. Holding maturity and moneyness constant alleviates this concern. Accordingly, we also use implied volatility of the stock taken from OptionMetrics' implied volatility surface. Panel C of Table 8 reports these post/pre-slit standardized IV ratios. We find again that both calls and puts are more expensive (as evidenced by higher IVs) post-split.[11]

Stock return volatility typically increases after splits (Ohlson and Penman (1985)). However, stock splits in our sample are anticipated events as the date of the split is announced well in advance. Therefore, pre-split implied volatility, which is a forward-looking measure of volatility (absent volatility risk premium effects) should already reflect the expectation of increased volatility. Even if the investors are unaware of the fact that volatility increases after split, our use of short windows around the event means that investors use the same expected volatility pre- and post-event (higher volatility if they are aware of the empirical patterns in volatility; lower volatility otherwise). In other words, over the short windows that we analyze, we do not expect changes in implied volatility of options. Our evidence of change in option prices (implied volatility), therefore, cannot be attributed to changes in realized volatility but, rather, is due to the behavioral biases that we discuss in this paper.

We also analyze abnormal option returns around stock splits. If options become more expensive due to investors' preferences for options with low underlying prices, then both calls and puts should exhibit positive abnormal returns around a stock split. We measure abnormal option returns as the return on the option's delta-hedged position minus the return on the equivalent position on the S&P 500 index. We calculate these excess returns over windows of one, three, and five days around the split. Panel D of Table 8 presents the results of this test. As expected, all option abnormal returns are positive. The results are stronger for puts than for calls. The abnormal returns to delta-hedged puts are highly statistically significant for all three return windows. For instance, the abnormal returns for delta-hedged puts are 1.30% over a five-day window around the stock split. For calls the results are weaker with abnormal returns being marginally statistically significant.

We also expect that the magnitude of abnormal returns should depend on the split ratio – the higher the split ratio, the greater the potential overpricing of options post-split. To

[11] Shue and Townsend (2019) also document an increase in implied volatility around splits. Their focus is on longer windows around the event. They attribute the increase in implied volatility to option traders not fully incorporating expected increase in realized volatility into their forecasts. See also Dubinsky, Johannes, Kaeck, and Seeger (2018) for the role of anticipated uncertainty in option pricing models.

formally test this prediction, we regress abnormal option returns on the logarithm of the split ratio and present results in Panel E of Table 8. We find that the coefficients on the split ratio are positive and highly significant for all windows. Economically, the effect of the split on option returns is large. For example, a change in the split ratio from two to ten would result in an increase in the abnormal returns to delta-hedged call and put portfolios over a $(-5, +5)$ day window around the split date of 10.7% to 11.9%.

3.2 Mini-index options

To further document the relation between option prices and underlying prices, we take advantage of another feature of the market, viz. options written on mini indexes. Mini-index options are a scaled down version of index options—they are index options with only one-tenth the contract size of regular index options. The lower cost of mini-index options gives small retail option traders a chance to get more involved in trading on the broader market.

Mini-index options were first introduced to the market in the form of Mini-NDX Index Options in the year 2000. Mini-NDX Index Options are options offered on a one-tenth scaled down index of the NDX (Nasdaq100) known as the MNX. Following the introduction of Mini-NDX, Mini-SPX Index Options were offered in 2005 on a one-tenth scaled down index of the SPX (S&P500) known as the XSP. Both options on the regular index and the mini-index options are European and the only difference between the two types of options is the scale-down factor.

The existence of mini-index options offers a unique opportunity to examine the hypothesis of investor inattention leading to option mispricing. Note that mini-index options offer an even cleaner setting than stock splits as there are no countervailing effects of signaling, changing fundamentals, or changing volatility of stocks post-split. Absent any behavioral biases, the prices of mini-index options should be one tenth of the prices of the regular index-options as the only difference between the regular index and the mini index is the scaling factor. Our central hypothesis H1 from Section 1.4 would imply, however, that mini-index options are relatively more expensive.

To analyze the difference between regular index and mini-index options, on each trading day, we match an option on the main index with an option on the mini index based on the expiration date and the adjusted strike price. We approximate prices at midpoint bid-ask quotes. For each pair of options, we compute the price ratio as:

$$\text{Price ratio} = \frac{\text{Mini-index option price} \times 10}{\text{Main-index option price}} \tag{15}$$

We include only options with moneyness (ratio of index to strike price) between 0.9 and 1.1. We present the results for different days to maturity in Table 9. We have about 70,000 observations for both call and put options.

We find that, for both put and call options, the scaled ratio of mini-index option price to main-index option price is greater than one (and highly statistically significantly different from one) indicating relative overpricing of mini index options. The only exception is call options with 91 to 180 days to maturity where the ratio is slightly lower than one (although statistically insignificantly so). We also find more mispricing for puts than that for calls. For example, the average overpricing is about 2.5% for call options, and about 6.3% for put options of less than 30 days to maturity. The mispricing is more pronounced for short-term options than for longer-dated options. Mispricing declines from 6.3% to 0.3% for put options with less than 30 days to maturity to those with 91 to 180 days to maturity.

To summarize, looking both at stock splits and mini-index options reveals similar patterns in the relation between option prices and underlying security prices, whereby options on securities with lower prices tend to be relatively overvalued, supporting the main hypothesis of our model.

4 Role of retail investors and hedging costs

Our model in Section 1 relies on limited-attention investors. Their excess demand coupled with the inability of risk-averse market makers to perfectly hedge their positions drives up the prices of options on low-priced stocks leading to subsequent low returns. Hypothesis H3 in Section 1.4 predicts that overpricing is increasing in the (relative) number of these limited-attention investors and hypothesis H4 predicts that overpricing is increasing in hedging costs of market makers. In this section, we provide evidence consistent with these predictions.

Who might be the limited-attention investors? There are different types of option traders with different levels of professionalism and sophistication (see Lakonishok et al. (2006) for a detailed analysis of the types of option investors). Conventional wisdom suggests that retail investors are likely to be less sophisticated and, hence, potentially more prone to behavioral biases than professional investors like hedge funds or corporations. We, therefore, posit that retail investors are closer to the limited-attention investors than to the rational investors in our model. Accordingly, we first perform three tests of the role of retail investors. First, we show that options on stocks with high institutional ownership are less mispriced as we observe lower profitability for trading options on these stocks. Second, we show that net buying of retail investors decreases as underlying stock price increases, while the reverse is true for institutional investors. Third, we show directly that net retail demand is related to option expensiveness.

In the last subsection, we test the effect of hedging costs on the relation between stock price and option expensiveness.

4.1 Institutional ownership

Institutional investors are more sophisticated and better informed than retail investors. They are also more likely to use rigorous theoretical models for the pricing of options. Therefore, hypothesis H3 from Section 1.4 predicts that mispricing of options due to limited-attention investors is weaker for options that are more heavily traded by institutions. We rely on institutional ownership of the underlying *equity* as a proxy for investor sophistication. While this measure is not a direct proxy for the sophistication of *option* traders, one might envision that options on stocks with higher institutional ownership are also more actively traded by institutions. Therefore, we expect less room for any behavioral biases in the pricing of options on stocks with high institutional ownership.

To test this conjecture, we rerun the FM regressions from Table 4 from Section 2.4. We add institutional ownership and its interaction with the logarithm of the underlying stock price to the list of independent variables. If, as we hypothesize, the relationship between option returns and the underlying stock price is weaker for stocks with high institutional ownership, one should expect a negative sign on the interaction term. The results from these regressions are reported in Table 10. We find positive and statistically significant coefficients on both the log stock price (as before) and institutional ownership. More important for our test, we find that the coefficient on the interaction term of institutional ownership and stock price is negative and highly statistically significant across all regression models. For the regression of delta-hedged calls with all controls, the coefficients on log stock price and the interaction terms are 0.938 and -0.299, respectively. This means that the effect of log price for stocks with 50% institutional ownership is only 84% ($= (0.938 - 0.299 \times 50\%)/0.938$) of that for stocks with zero institutional ownership. The equivalent number for put options is 79%. Our results, thus, show that institutional ownership (of underlying stocks) helps to ameliorate option mispricing related to stock price.

4.2 Retail traders' demand

We obtain data from International Securities Exchange (ISE), which contain the complete daily records of option buy and sell activities of different market participants since 2009.

Ge, Lin, and Pearson (2016) report that ISE trades represent about 30% of the total trading volume on individual equity options. Following the literature, we compute total net buy as the difference between the total daily buy and sell trade positions (measured by both trading volume and number of trades), divided by the total daily trade positions. Similarly, we compute the measures of net buy separately for retail and professional investors. Following the literature, we classify all types of customer traders as retail investors, and proprietary traders and brokers/dealers as professional investors. Market clearing implies that market makers take the opposite side and the sum of retail and professional trades is equal to market maker volume. In addition to looking at all positions, we also examine only the opening positions, as these positions might be more indicative of investors' trading activity on a given date (Pan and Poteshman (2006)).

We run cross-sectional FM regressions of these measures of net buy by all (retail, professional) investors on the logarithm of the underlying stock price and a set of the same control variables as in Table 4. If professional option traders (partly) recognize the mispricing of options due to the effect of the underlying stock prices, they are more likely to prefer to buy options on stocks with higher prices (that appear to be underpriced) and sell options on stocks with lower prices (that appear to be overpriced). Therefore, we expect a positive coefficient on stock price for regressions of professional trades. By contrast, we expect a negative coefficient on stock price for regressions of retail trades.

For the sake of brevity, we only report the coefficients on our main variable of interest, the logarithm of the stock price. These coefficients are reported in Table 11. We find that all our measures of net buy (based on all positions as well as opening positions and using total trading volume as well as the number of trades) for professional investors are positively and highly statistically significantly associated with the underlying stock prices. This relationship is reversed for retail investors; for this group of investors there is more buying for options on low-priced stocks. The coefficients for opening positions are slightly higher (in absolute value) than those for all positions. Therefore, there is also some evidence in our tests that opening positions are more informative than other positions.

4.3 Option demand and option expensiveness

We have already shown that decile one options are more expensive than decile ten options, and that options in decile one have excess retail demand. In this section, we tie these findings together by showing that it is the excess demand from retail investors that leads to option expensiveness. We follow GPP (2009) in measuring the net demand as net open interest. We consider stocks with strictly positive trading volume on at least 80% of days over the last year. For each of these stocks on each trading date we include all options (calls and puts) with 15 to 45 calendar days to expiration and moneyness between 0.95 and 1.05. For each of those options, we use the ISE database for classifications of open/close and buy/sell trading volume made by retail investors. We then measure the retail daily buy/sell open interest using the recursive equations starting from the first day of the option trade, following Ni, Pearson, Poteshman, and White (2021):

$$\begin{aligned}
\text{OpenInterest}^{\text{Buy}}_{j,t} &= \text{OpenInterest}^{\text{Buy}}_{j,t-1} + \text{Volume}^{\text{Open Buy}}_{j,t} - \text{Volume}^{\text{Close Sell}}_{j,t} \\
\text{OpenInterest}^{\text{Sell}}_{j,t} &= \text{OpenInterest}^{\text{Sell}}_{j,t-1} + \text{Volume}^{\text{Open Sell}}_{j,t} - \text{Volume}^{\text{Close Buy}}_{j,t}
\end{aligned} \tag{16}$$

for option j on trading day t. The retail investors' net demand on day t is then defined as the difference between the retail buy and sell open interest. We aggregate the net demand of all options for each trading day in a month to obtain the retail net demand at the monthly frequency for each firm. GPP consider "weighting" net demands based on different kinds of unhedgeable risks. We explicitly consider the effect of hedging costs in the next subsection. In this subsection, we follow GPP and multiply the demand by options gamma (to capture impossibility of continuous time trading) or vega (to capture stochastic volatility risk) before aggregating to the monthly level. Finally, the aggregate monthly net demand is scaled by firm's number of shares outstanding to make the measures comparable across firms. In short, we consider three measures of net demand: raw, gamma-weighted, and vega-weighted.

Option expensiveness is measured as the difference between the option's implied volatility and the expected volatility derived from the GARCH(1,1) model based on the past 60 months (see GPP (2009)). We average the option expensiveness for each trading day in the month, and then average across all trading days in the month to get the firm's option expensiveness at a monthly frequency.

We finally run cross-sectional FM regressions of option expensiveness on net demand. The control variables are also motivated by GPP (2009). These include the total trading volume of the options on the firm's stock during the month, the return on the firm's stock in the past month, and the past volatility of the stock return, measured by the standard deviation of the daily returns over the past year. We run these regressions separately for deciles one and ten of stock price. Given our earlier evidence in Table 11 of excess demand for options in decile one, we expect to see a positive coefficient on net demand for decile one and a smaller (or zero) coefficient for decile ten.

Table 12 presents the results. We find that option expensiveness is positively related to option volume. This is prima-facie evidence in support of GPP (2009). We also find that option expensiveness is negatively related to past stock return and stock volatility for both deciles one and ten although the coefficients are statistically significant only for decile ten. The coefficient of interest to us is the one on net retail investor demand. We find that option expensiveness is positively related to investor demand for decile one. All coefficients are statistically significant regardless of the way we measure net demand. In contrast, coefficient on net demand is small and statistically insignificant for decile ten for raw net demand and vega-weighted net demand. The only exception is that option expensiveness is positively related to gamma-weighted net demand for decile ten.

4.4 Hedging costs

Hypothesis H4 in Section 1.4 implies that the returns to options written on low-priced stocks should be higher when it is more difficult to hedge the option returns against stock price movements. To assess whether the low-price effect we document is more pronounced amongst option positions that require higher hedging costs, we analyze returns on double-sorted portfolios. Each month we first sort all options into five equal-sized quintiles according to three hedging costs proxies: stock bid-ask spread (measured by the average daily bid-ask spread in the previous month), stock illiquidity, and idiosyncratic volatility (see, for example, De Fontnouvelle, Fishe, and Harris (2003), Engle and Neri (2010), Hu (2021), Jameson and Wilhelm (1992), and Muravyev and Pearson (2020)). We then sort the options further into deciles according to the market price of the underlying stock. This yields fifty portfolios on the hedging costs/stock price dimensions. For each hedging cost quintile, we examine the difference in returns between the two extreme stock price deciles. The prediction is that the returns to the long-short portfolio should increase from quintile Q1 to quintile Q5 as (the proxy for) hedging costs increases.

The results reported in Table 13 provide evidence consistent with this prediction. The 7-factor alpha of the high-minus-low stock price portfolio is generally increasing when moving from the low to the high hedging costs quintile. For example, the alpha for delta-hedged calls is 0.57% for Q5 of stocks with the highest bid-ask spread but a minuscule 0.01% for Q1 of stocks with the lowest bid-ask spread. The alpha is always economically strong and statistically significant for quintile Q5 and economically smaller for quintile Q1, suggesting that in the absence of hedging costs, market makers price options correctly regardless of demand pressure from (limited-attention) investors. In fact, we find that in all cases the alpha of the quintile Q5 is at least twice as much than that of quintile Q4. These results, therefore, show that lack of perfect hedging by market makers is a necessary ingredient for demand pressure to have an impact on option prices. Overall, the results in this section provide further support for our model's implications.

5 Conclusion

We document a new effect in options prices – equity options written on securities with lower prices tend to be relatively overpriced. This overpricing is manifested in delta-hedged call and put portfolio returns, in returns to portfolios double sorted on the underlying price and various stock characteristics as well as in cross-sectional FM regressions. We show, via a rigorous theoretical model, that this bias arises due to investors' perception of such options as "good deals" due to inattention to their underlying stock prices.

Our results are robust to using an alternative measure of mispricing based on the difference between market and theoretical Black-Scholes option values. We also take advantage of stock splits and mini index options and find relative overpricing of options post-split and also of mini index options (relative to regular index options). Consistent with retail investors being relatively less sophisticated and, therefore, more prone to behavioral biases, we find that the relation between option returns and underlying prices is stronger for stocks with low institutional ownership. We also find that the effect is stronger for options traded more heavily by retail traders, and for options on stocks where hedging costs are higher.

Appendix

A Proofs

A.1 R's and LA's expectations

Since the stock price follows a geometric Brownian motion with drift μ and volatility σ, standard results show that the stock price at maturity T is given by

$$S_T = S_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)T + \sigma Z_T\right),$$

and that the Black-Scholes price of an ATM call option is given by $v_0 = \theta_0 S_0$ where $\theta_0 = N(d_1) - N(d_2)$ (recall that we have normalized the risk-free rate to zero), $d_1 = 0.5\sigma\sqrt{T}$, $d_2 = -0.5\sigma\sqrt{T}$, and $N(\cdot)$ is the cdf of the standard normal distribution. Similarly, it is straightforward to show that the expectation of the option payoff at maturity under the physical measure is given by:

$$\mathrm{E}\left[(S_T - K)^+\right] = S_0\theta(\mu, \sigma, T),$$

where $\theta(\mu, \sigma, T) = e^{\mu T}N(\widehat{d}_1) - N(\widehat{d}_2)$, $\widehat{d}_1 = \mu/\sigma\sqrt{T} + 0.5\sigma\sqrt{T}$, and $\widehat{d}_2 = \widehat{d}_1 - \sigma\sqrt{T}$.

Therefore, the expectations of the option payoff for the R and LA agents are given by:

$$\begin{aligned} \mathrm{E}_R(v_T) &= \mathrm{E}\left[(S_T - K)^+ \middle| S_0\right] = S_0\theta_R(\mu, \sigma, T), \\ \mathrm{E}_{L,j}(v_T) &= \mathrm{E}\left\{\mathrm{E}\left[(S_T - K)^+ \middle| S_0\right] \middle| S_{L,j}\right\} = \widehat{S}_{0,j}\theta_L(\mu, \sigma, T), \end{aligned} \tag{A1}$$

where $\theta_R(\cdot) = \theta(\cdot)$ and $\theta_L(\cdot) = e^{0.5\sigma_L^2}\theta(\cdot)$. We took into account that, for the LA agent, $S_0 = \widehat{S}_{0,j}e^{\sigma_L u_j}$, as follows from (2). This proves the first two lines of equation (5).

Similarly, it follows that the variance of the option payoff is given by:

$$\mathrm{Var}\left[(S_T - K)^+\right] = S_0^2 F_R(\mu, \sigma, T),$$

where

$$\begin{aligned} F_R(\mu, \sigma, T) &= e^{2\mu T}\left(e^{\sigma^2 T}N(\widehat{d}_0) - N^2(\widehat{d}_1)\right) + N(\widehat{d}_2)\left(1 - N(\widehat{d}_2)\right) \\ &\quad -2e^{\mu T}N(\widehat{d}_1)\left(1 - N(\widehat{d}_2)\right), \end{aligned}$$

with $\widehat{d}_0 = \widehat{d}_1 + \sigma\sqrt{T}$. Therefore, the variances of the option payoff for R and LA agents are given by:

$$\begin{aligned}
\mathrm{Var}_R(v_T) &= \mathrm{E}\left[\left((S_T-K)^+\right)^2 \middle| S_0\right] - \left(\mathrm{E}\left[(S_T-K)^+ \middle| S_0\right]\right)^2 \\
&= S_0^2 F_R(\mu,\sigma,T), \\
\mathrm{Var}_{L,j}(v_T) &= \mathrm{E}\left\{\mathrm{E}\left[\left((S_T-K)^+\right)^2 \middle| S_0\right] \middle| S_{L,j}\right\} - \left(\mathrm{E}\left\{\mathrm{E}\left[(S_T-K)^+ \middle| S_0\right] \middle| S_{L,j}\right\}\right)^2 \\
&= \widehat{S}_{0,j}^2 F_L(\mu,\sigma,T), \qquad \text{(A2)}
\end{aligned}$$

where

$$\begin{aligned}
F_L(\mu,\sigma,T) &= e^{2\mu T+2\sigma_L^2}\left(e^{\sigma^2 T}N(\widehat{d}_0) - N^2(\widehat{d}_1)e^{-\sigma_L^2}\right) + e^{2\sigma_L^2}N(\widehat{d}_2)\left(1-N(\widehat{d}_2)e^{-\sigma_L^2}\right) \\
&\quad -2e^{2\mu T+2\sigma_L^2}N(\widehat{d}_1)\left(1-N(\widehat{d}_2)e^{-\sigma_L^2}\right),
\end{aligned}$$

which proves the last two lines of equation (5).

A.2 Market makers' variance

Equation (7) shows that change in MM's portfolio per unit of option is given by:

$$\Delta\pi_t = \frac{1}{\sqrt{2}}S_t^2\sigma^2\Gamma_t\Delta t\eta_t + o(\Delta t)$$

The total variance of the MMs position per unit of option is:

$$\begin{aligned}
\mathrm{Var}_M(\pi_T) &\simeq \frac{1}{2}\sigma^4(\Delta t)^2\sum_{k=0}^{N}\mathrm{E}\left(S_{t_k}^4\Gamma_{t_k}^2\eta_{t_k}^2\right) \simeq \frac{1}{2}\sigma^4(\Delta t)^2\frac{1}{\Delta t}\int_0^T \mathrm{E}\left(S_t^4\Gamma_t^2\right)\overline{\eta_t^2}dt \\
&= \frac{1}{2}\sigma^4\Delta t\int_0^T \mathrm{E}\left(S_t^4\Gamma_t^2\right)dt = \frac{1}{2}\sigma^4\Delta t\int_0^T \mathrm{E}\Psi_t^2 dt \qquad \text{(A3)}
\end{aligned}$$

where $\overline{\eta_t^2} = \mathrm{E}\eta_t^2$, η_t is defined in footnote 1, and $\Psi_t \equiv S_t^2\Gamma_t$. We took into account that $\overline{\eta_t^2} = 1$ and applied Fubini's theorem in the second line.

Given our normalization of zero risk-free rate, the Black-Scholes option value v_t satisfies the well-known PDE:

$$\frac{\partial v_t}{\partial t} + \frac{\sigma^2}{2}S_t^2\frac{\partial^2 v_t}{\partial S_t^2} = 0.$$

Note that we do not assume that the actual option price equals the Black-Scholes one, but we need to track the Black-Scholes values in order to be able to compute the option's Greeks that determine the MMs hedging strategies (as we discuss above, we assume that MMs ignore the effect of the imperfect hedging on their hedging strategies). Applying an operator $D = S^2\frac{\partial^2}{\partial S^2}$ to the above equation, we obtain that Ψ satisfies the same PDE:

$$\frac{\partial \Psi_t}{\partial t} + \frac{\sigma^2}{2}S_t^2\frac{\partial^2 \Psi_t}{\partial S_t^2} = 0.$$

and hence Ψ has a martingale property similar to v_t:

$$d\Psi_t = \left(\frac{\partial \Psi_t}{\partial t} + \frac{\sigma^2}{2} S_t^2 \frac{\partial^2 \Psi_t}{\partial S_t^2}\right) dt + \sigma S_t \frac{\partial \Psi_t}{\partial S_t} dZ_t = \sigma S_t \frac{\partial \Psi_t}{\partial S_t} dZ_t. \tag{A4}$$

Since Ψ_t is a martingale, we can apply the Feynman-Kac method to evaluate it. Note that the boundary condition at maturity is: $\Psi_T = S_T^2 \delta(S_T - K)$, where $\delta(\cdot)$ is a Dirac's delta function. Taking into account that $S_T = S_t \exp\left(-\frac{\sigma^2}{2}(T-t) + \sigma Z_{T-t}\right)$, we obtain:

$$\begin{aligned}
\Psi_t &= \mathrm{E}\left[S_T^2 \delta\left(S_t \exp\left(-\frac{\sigma^2}{2}(T-t) + \sigma Z_{T-t}\right) - K\right)\right] \\
&= K\mathrm{E}\left[\delta\left(\exp\left(\ln S_t - \ln K - \frac{\sigma^2}{2}(T-t) + \sigma Z_{T-t}\right) - 1\right)\right] \\
&= \frac{K}{\sqrt{2\pi\sigma^2(T-t)}} \exp\left(-\frac{\left(\ln S_t - \ln K - \frac{\sigma^2}{2}(T-t)\right)^2}{2\sigma^2(T-t)}\right),
\end{aligned} \tag{A5}$$

and its unconditional expectation is given by:

$$\begin{aligned}
\mathrm{E}\Psi_t^2 &= \frac{K^2}{2\pi\sigma^2(T-t)} \mathrm{E}\left[\exp\left(-\frac{\left(\ln S_0 - \ln K - \frac{\sigma^2}{2}T + \sigma Z_t\right)^2}{\sigma^2(T-t)}\right)\right] \\
&= \frac{K^2}{2\pi\sigma^2\sqrt{T^2-t^2}} \exp\left(-\frac{\left(\ln S_0 - \ln K - \frac{\sigma^2}{2}T\right)^2}{\sigma^2(T+t)}\right) \\
&= \frac{S_0^2}{2\pi\sigma^2\sqrt{T^2-t^2}} \exp\left(-\frac{\sigma^2 T^2}{4\,(T+t)}\right),
\end{aligned} \tag{A6}$$

where we took into account that $S_t = S_0 \exp\left(-\frac{\sigma^2}{2}t + \sigma Z_t\right)$, and the last line applies for the ATM call $K = S_0$. Substituting this back into equation (A3), we obtain:

$$\begin{aligned}
\mathrm{Var}_M(\pi_T) &= S_0^2 \frac{\sigma^2 \Delta t}{4\pi} \int_0^T \frac{dt}{\sqrt{T^2-t^2}} \exp\left(-\frac{\sigma^2 T^2}{4(T+t)}\right) \\
&= S_0^2 \frac{\sigma^2 \Delta t}{4\pi} \int_0^1 \frac{d\xi}{\sqrt{1-\xi^2}} \exp\left(-\frac{\sigma^2 T}{4\,(1+\xi)}\right) \\
&= S_0^2 \Phi(\sigma^2 T/4)/N,
\end{aligned} \tag{A7}$$

where we introduced a dummy integration variable $\xi = t/T \in (0,1)$ and the function $\Phi(x)$ is defined as

$$\Phi(x) = \frac{x}{\pi} \int_0^1 \frac{d\xi}{\sqrt{1-\xi^2}} \exp\left(-\frac{x}{1+\xi}\right), \tag{A8}$$

which proves equation (8).

A.3 Market clearing

Aggregating demand and supply and applying the market clearing condition $N_R y_R + \sum_{j=1}^{N_L} y_{L,j} = N_M y_M$, we obtain:

$$N_R \frac{S_0 \theta_R(\mu,\sigma,T) - P_0}{\alpha_R S_0^2\, F_R(\mu,\sigma,T)} + \sum_{j=1}^{N_L} \frac{\widehat{S}_{0,j}\theta_L(\mu,\sigma,T) - P_0}{\alpha_L \widehat{S}_{0,j}^2 F_L(\mu,\sigma,T)} = N_M \frac{P_0 - S_0\theta_0}{S_0\sqrt{8\chi\alpha_M \Phi(\sigma^2 T/4)}} \tag{A9}$$

Recall that $\widehat{S}_{0,j} = \left(\overline{S}\right)^{1-k}\left(S_{L,j}\right)^k$, and $S_{L,j} = S_0 e^{\sigma_\epsilon \epsilon_j}$. Denote $\widehat{S}_0 = \left(\overline{S}\right)^{1-k}\left(S_0\right)^k$. Then

$$\begin{aligned} \sum_{j=1}^{N_L} \frac{\widehat{S}_{0,j}\theta_L(\mu,\sigma,T) - P_0}{\alpha_L \widehat{S}_{0,j}^2 F_L(\mu,\sigma,T)} &\simeq N_L \frac{\mathrm{E}_z\left[\widehat{S}_0 e^{-k\sigma_\epsilon z}\theta_L(\mu,\sigma,T) - P_0 e^{-2k\sigma_\epsilon z}\right]}{\alpha_L \widehat{S}_0^2 F_L(\mu,\sigma,T)} \\ &= N_L \frac{\left(\widehat{S}_0 e^{0.5k^2\sigma_\epsilon^2}\theta_L(\mu,\sigma,T) - P_0 e^{2k^2\sigma_\epsilon^2}\right)}{\alpha_L \widehat{S}_0^2 F_L(\mu,\sigma,T)} \\ &= N_L \frac{\widehat{S}_0 \widehat{\theta}_L(\mu,\sigma,T) - P_0}{\alpha_L \widehat{S}_0^2 \widehat{F}_L(\mu,\sigma,T)}, \end{aligned} \tag{A10}$$

where $\widehat{\theta}_L(\mu,\sigma,T) = e^{-1.5k^2\sigma_\epsilon^2}\theta_L(\mu,\sigma,T)$ and $\widehat{F}_L(\mu,\sigma,T) = e^{-2k^2\sigma_\epsilon^2}F_L(\mu,\sigma,T)$. In the first line of (A10), we took into account that the number of LA agents is large, and hence by the law of large numbers the sum can be approximated by the expectation.

It follows from (A9) and (A10) that the market clearing price is given by:

$$P_0 = (1 - \gamma_R - \gamma_L)\, S_0\theta_0 + \gamma_R S_0 \theta_R + \gamma_L \widehat{S}_0 \widehat{\theta}_L, \tag{A11}$$

with

$$\begin{aligned} \gamma_R &= \frac{N_R}{\alpha_R S_0^2 F_R(\mu,\sigma,T)} \Bigg/ \left(\frac{N_R}{\alpha_R S_0^2 F_R(\mu,\sigma,T)} + \frac{N_L}{\alpha_L \widehat{S}_0^2 \widehat{F}_L(\mu,\sigma,T)} + \frac{N_M}{S_0\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}}\right) \\ \gamma_L &= \frac{N_L}{\alpha_L \widehat{S}_0^2 \widehat{F}_L(\mu,\sigma,T)} \Bigg/ \left(\frac{N_R}{\alpha_R S_0^2 F_R(\mu,\sigma,T)} + \frac{N_L}{\alpha_L \widehat{S}_0^2 \widehat{F}_L(\mu,\sigma,T)} + \frac{N_M}{S_0\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}}\right). \end{aligned}$$

Then the mispricing of the call option (with $v_0 = S_0\theta_0$) is defined as

$$\frac{P_0 - v_0}{v_0} = \gamma_R \left(\frac{\theta_R(\mu,\sigma,T)}{\theta_0(\sigma,T)} - 1\right) + \gamma_L \left(\frac{\widehat{S}_0}{S_0}\frac{\widehat{\theta}_L(\mu,\sigma,T)}{\theta_0(\sigma,T)} - 1\right). \tag{A12}$$

When the drift μ is small, $(\mu - r_f)/\sigma^2 \ll 1$ (as is typically the case for most stocks with short maturity options) $\theta_R(\mu,\sigma,T)\simeq\theta_0(\sigma,T)$. In this case equation (A12) simplifies to:

$$\frac{P_0-v_0}{v_0}=\frac{\eta\left(\frac{\overline{S}}{S_0}\right)^{1-k}-1}{1+\frac{N_R}{N_L}\frac{\alpha_L}{\alpha_R}\frac{\widehat{F}_L(0,\sigma,T)}{F_R(0,\sigma,T)}\left(\frac{\overline{S}}{S_0}\right)^{2(1-k)}+\frac{N_M}{N_L}\frac{\alpha_L\widehat{F}_L(0,\sigma,T)\overline{S}}{\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}}\left(\frac{\overline{S}}{S_0}\right)^{1-2k}}, \tag{A13}$$

where we define $\eta=e^{0.5\sigma_L^2-1.5k^2\sigma_\epsilon^2}=e^{0.5\sigma_0^2(1-k)(1-3k)}$. It follows that misrpicing is positive (call options are overpriced) when $S_0<\overline{S}\eta^{\frac{1}{1-k}}$, and is negative (call options are underpriced) when $S_0>\overline{S}\eta^{\frac{1}{1-k}}$.

Define $A=\frac{N_R}{N_L}\frac{\alpha_L}{\alpha_R}\frac{\widehat{F}_L(0,\sigma,T)}{F_R(0,\sigma,T)}$, $B=\frac{N_M}{N_L}\frac{\alpha_L\widehat{F}_L(0,\sigma,T)\overline{S}}{\sqrt{8\chi\alpha_M\Phi(\sigma^2T/4)}}$, $p=\frac{1-2k}{1-k}$, and $x=\left(\frac{\overline{S}}{S_0}\right)^{1-k}$, the mispricing equation (A13) can be rewritten as:

$$\frac{P_0-v_0}{v_0}=\eta\phi(x)=\eta\frac{x-\frac{1}{\eta}}{1+Ax^2+Bx^p}. \tag{A14}$$

Thus, the mispricing depends on three parameters: A, B, and k. The parameters A and B depend on the number of LA agents and their risk aversion relative to the number and risk aversion of the rational (R) agents and the number, risk aversion and hedging costs of the market makers (MM), respectively. The parameter $k\in[0;1]$ defines both η and p and reflects the degree of inattentiveness of the LA agents. In particular, in the limit $k\to 1$ the LA agents become rational, while the opposite limit $k\to 0$ corresponds to complete inattention when the LA agents acquire their information from the distribution of stock prices.

Differentiating equation (A14) w.r.t. x, we obtain

$$\phi'(x)=\frac{1+\frac{2A}{\eta}x-Ax^2+B(1-p)x^p+\frac{Bp}{\eta}x^{p-1}}{\left(1+Ax^2+Bx^p\right)^2}, \tag{A15}$$

and $\phi'(x)>0$ iff

$$1+\frac{2A}{\eta}x-Ax^2+B(1-p)x^p+\frac{Bp}{\eta}x^{p-1}>0. \tag{A16}$$

When the number of LA agents is relatively small, $N_L\ll N_R$ and the degree of inattention is low, $1-k\ll 1$, the sign of equation (A16) is determined by the first three terms. Analyzing the quadratic function given by the first three terms, we obtain that equation (A16) is positive if $x<x_m=\frac{1}{\eta}+\sqrt{\frac{1}{\eta^2}+\frac{1}{A}}$. In the limit of small $\frac{N_L}{N_R}$, we have $x_m\approx\frac{2}{\eta}$. Recalling that $x=\left(\overline{S}/S_0\right)^{1-k}$, we conclude that the mispricing is monotonically increasing in x and hence *decreasing* in S_0, if $S_0>S_0^*$ where $S_0^*\approx\overline{S}\left(\frac{\eta}{2}\right)^{\frac{1}{1-k}}\ll\overline{S}$.

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Table 1: Summary statistics

The data on options are from the OptionMetrics Ivy DB database over the period 1996 to 2017. Data on the underlying stocks are obtained from CRSP/Compustat. The sample includes data on all options as of the option expiration day in each month, i.e., the third Friday of the month. The selected options are those that expire in the following month. For each underlying security in each month, we pick the call and the put options that are closest to at-the-money, as long as the moneyness (ratio of stock price to strike price) is between 0.7 and 1.3. We exclude options with zero open interest or trading volume. The final sample includes 257,107 call options and 204,123 put options. Each month we sort all options into ten equal-sized deciles according to the market price of the underlying stock. The table reports statistics of the characteristics of the options as well as their underlying stocks for the full sample and separately for the top and bottom deciles (decile 1 = lowest stock prices, decile 10 = highest stock prices). All variables are winsorized at the 1st and 99th percentiles. For each variable, we first calculate the cross-sectional mean and median across stocks for each portfolio. We then report the time-series averages of these means/medians. Size is the equity value of the underlying stock (in billions of dollars). Market-to-book of the underlying stock is the ratio of current equity market value to equity book value as of the previous quarter. Past return of the underlying stock is cumulative return over the past six months. Profitability is the annual income before extraordinary items divided by the previous year's book equity value. Analyst forecast dispersion is the ratio of the standard deviation of analyst earnings forecast to the absolute value of the consensus mean forecast; for each firm-month we use the average dispersion over the previous three months. Net shares issuance (in percent) is measured by the annual log change in split-adjusted shares outstanding. Illiquidity of the underlying stock is the Amihud's (2002) measure, calculated by the monthly average of daily ratios of absolute return to dollar trading volume (in millions). IVOL, ISKEW, and IKURT are the standard deviation, skewness, and kutrtosis of the residuals from regressions of daily stock returns on the Fama-French (1993) three factors in the past three months, and MAX10 is the average of the highest 10 daily returns during that period. Volume/open interest is the ratio of the daily trading volume to open interest of the option. Option bid-ask spread is the difference between the ask and bid quotes of the option over the midpoint of bid and ask quotes at the end of the trading day. Implied volatilities are provided by OptionMetrics. IV-HV is the difference between the option's implied volatility and historical volatility, based on daily returns over the past year. Gamma and Vega are Black-Scholes option derivatives.

		Calls			Puts		
		All	Decile 1	Decile 10	All	Decile 1	Decile 10
Stock price	Mean	42.24	7.31	141.66	45.16	7.91	157.67
	Median	31.23	7.44	97.13	32.81	8.07	102.06
Option price	Mean	1.86	0.60	5.07	1.94	0.74	5.11
	Median	1.36	0.53	3.65	1.44	0.65	3.76
Size	Mean	11.40	1.15	32.19	13.39	1.49	35.76
	Median	2.73	0.46	14.39	3.32	0.57	16.42
Market-to-book	Mean	3.35	2.45	4.35	3.42	2.42	4.42
	Median	2.84	1.75	4.26	2.94	1.73	4.34
Past stock return	Mean	0.106	−0.016	0.216	0.099	−0.027	0.221
	Median	0.060	−0.095	0.166	0.051	−0.112	0.169
Profitability	Mean	0.099	−0.143	0.222	0.113	−0.114	0.228
	Median	0.139	−0.039	0.205	0.145	−0.021	0.210
Analyst forecast dispersion	Mean	0.081	0.078	0.061	0.081	0.078	0.061
	Median	0.059	0.100	0.043	0.060	0.100	0.045
Net shares issuance	Mean	3.69	8.11	1.91	3.59	8.10	1.85
	Median	0.97	2.58	0.38	0.95	2.67	0.39
Stock illiquidity	Mean	0.357	1.491	0.037	0.263	1.080	0.031
	Median	0.091	0.840	0.015	0.067	0.549	0.013
IVOL	Mean	0.024	0.038	0.016	0.024	0.038	0.016
	Median	0.021	0.035	0.014	0.021	0.034	0.015
ISKEW	Mean	0.222	0.268	0.271	0.187	0.211	0.267
	Median	0.203	0.329	0.163	0.181	0.293	0.163
IKURT	Mean	3.804	4.511	3.126	3.831	4.592	3.191
	Median	1.557	2.142	1.204	1.561	2.204	1.230
MAX10	Mean	0.044	0.066	0.033	0.044	0.065	0.034
	Median	0.040	0.061	0.030	0.039	0.060	0.031
Option volume/open interest	Mean	0.504	0.478	0.539	0.587	0.537	0.621
	Median	0.143	0.127	0.187	0.172	0.152	0.222
Option bid-ask spread	Mean	0.199	0.348	0.118	0.178	0.291	0.109
	Median	0.131	0.259	0.080	0.121	0.219	0.077
Implied volatility	Mean	0.460	0.724	0.325	0.471	0.732	0.336
	Median	0.423	0.706	0.306	0.432	0.708	0.316
IV−HV	Mean	0.023	0.073	0.010	0.032	0.076	0.020
	Median	0.027	0.087	0.016	0.035	0.085	0.026
Gamma	Mean	0.139	0.304	0.052	0.129	0.283	0.047
	Median	0.113	0.277	0.048	0.105	0.258	0.044
Vega	Mean	0.045	0.008	0.147	0.048	0.008	0.158
	Median	0.033	0.008	0.108	0.035	0.008	0.113

Table 2: Delta-hedged option portfolio returns sorted on underlying stock price

Portfolios are sorted as in Table 1 (decile 1 = lowest stock price, decile 10 = highest stock price). For each option we calculate the average weekly returns on delta-hedged position, based on market prices at option expiration day in a month and the position's payoff at the option maturity day in the next month. For delta-hedged calls the return is the gain during the investment period scaled by $(\Delta_C S - C)$, and for delta-hedged puts the return is the gain during the investment period scaled by $(P - \Delta_P S)$, where S, C, and P are the stock, call, and put option prices. The table shows the portfolios' equal-weighted mean excess weekly returns (in excess of the risk-free rate) and alphas from a 7-factor model. The factors are the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. The last column shows value-weighed returns/alphas on the 10−1 portfolio, where the weighting is according to the market value of the option's open interest (opt-vw). All returns and alphas are in percent per week and the corresponding t-statistics are in parentheses. The sample period is 1996 to 2017.

	1	2	3	4	5	6	7	8	9	10	10−1	10−1 opt-vw
Panel A: Delta-hedged calls												
Average return	−0.68	−0.35	−0.29	−0.22	−0.24	−0.23	−0.21	−0.19	−0.18	−0.14	0.54	0.46
	(−9.76)	(−6.18)	(−5.80)	(−4.92)	(−5.40)	(−5.41)	(−4.96)	(−4.86)	(−4.55)	(−3.17)	(9.66)	(5.34)
7-factor alpha	−0.55	−0.23	−0.19	−0.12	−0.15	−0.14	−0.11	−0.11	−0.09	−0.06	0.50	0.39
	(−9.44)	(−5.12)	(−4.91)	(−3.63)	(−4.41)	(−4.49)	(−3.82)	(−4.04)	(−3.27)	(−1.67)	(8.70)	(4.37)
Panel B: Delta-hedged puts												
Average return	−0.46	−0.28	−0.24	−0.20	−0.22	−0.18	−0.18	−0.17	−0.16	−0.12	0.34	0.31
	(−8.59)	(−6.38)	(−5.72)	(−4.90)	(−5.54)	(−4.53)	(−4.80)	(−4.51)	(−4.46)	(−2.91)	(7.64)	(4.22)
7-factor alpha	−0.37	−0.20	−0.16	−0.11	−0.14	−0.11	−0.11	−0.10	−0.09	−0.05	0.32	0.30
	(−8.17)	(−5.61)	(−4.88)	(−3.69)	(−4.78)	(−3.71)	(−3.84)	(−3.69)	(−3.47)	(−1.49)	(7.09)	(3.90)

Table 3: Delta-hedged option portfolio returns controlling for stock characteristics

Each month, we first sort all options into quintiles based on a stock characteristic. The options are then further sorted into deciles according to the market price of the underlying stock, yielding fifty characteristic/stock price portfolios. Delta-hedged option returns are calculated as in Table 2. We average returns for each stock price decile across the characteristic quintiles, yielding ten quintile-mean decile returns. The "Baseline results" refer to the single-sort results in Table 2. The table reports the 7-factor alpha of the 10−1 portfolio. The factors are the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. All alphas are in percent per week and the corresponding t-statistics are in parentheses. The sample period is 1996 to 2017.

	Delta-hedged calls	Delta-hedged puts
Baseline results	0.50	0.32
	(8.70)	(7.09)
Sorting characteristic		
Size	0.26	0.19
	(5.16)	(4.07)
Market-to-book	0.42	0.30
	(8.13)	(7.12)
Past stock return	0.41	0.30
	(8.28)	(7.32)
Profitability	0.33	0.25
	(5.75)	(5.34)
Forecast dispersion	0.29	0.20
	(5.33)	(4.25)
Net equity issuance	0.37	0.27
	(6.81)	(5.55)
IVOL	0.27	0.18
	(5.08)	(4.13)
ISKEW	0.40	0.29
	(7.24)	(6.15)
MAX10	0.26	0.19
	(5.32)	(4.60)
Stock illiquidity	0.26	0.17
	(5.45)	(4.20)
Option bid-ask spread	0.44	0.25
	(8.04)	(5.74)

Table 4: Fama-MacBeth regressions of delta-hedged option returns

Each month we run cross-sectional Fama and MacBeth (1973) regressions of the delta-hedged weekly option returns. The main independent variable is the log of the underlying stock price. The control variables include option and stock characteristics as described in Table 1. All coefficients are multiplied by 100 and Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample period is 1996 to 2017.

	Delta-hedged calls	Delta-hedged puts
Intercept	−2.444	−1.903
	(−5.98)	(−5.42)
Log(stock price)	0.745	0.587
	(7.51)	(7.19)
IVOL	1.778	0.046
	(0.74)	(0.02)
ISKEW	0.002	−0.002
	(0.31)	(−0.32)
IKURT	−0.005	−0.004
	(−3.55)	(−2.30)
MAX10	1.799	2.162
	(1.30)	(1.68)
Option volume/open interest	0.000	0.003
	(0.05)	(0.46)
Option bid-ask spread	−0.276	−0.162
	(−4.01)	(−2.72)
IV−HV	−0.287	−0.156
	(−3.88)	(−2.41)
Gamma	4.096	3.789
	(6.14)	(6.48)
Vega	−6.029	−3.421
	(−5.36)	(−4.34)
Log(size)	−0.043	−0.043
	(−5.00)	(−5.63)
Log(market-to-book)	−0.029	−0.033
	(−2.29)	(−1.96)
Past stock return	−0.051	−0.073
	(−1.17)	(−2.06)
Profitability	0.026	0.037
	(1.32)	(1.90)
Forecast dispersion	0.017	0.063
	(0.65)	(2.18)
Net equity issuance	−0.029	0.064
	(−0.37)	(0.85)
Stock illiquidity	−7.890	−7.603
	(−4.55)	(−3.08)

Table 5: Alternative measures of mispricing

Each month we run cross-sectional Fama and MacBeth (1973) regressions of the log of the ratio of the theoretical Black-Scholes option value to the actual option value. The Black-Scholes values are based on historical volatility of the underlying stock return or conditional expected volatility derived from the GARCH(1,1) model applied to monthly returns. The main independent variable is the log of the underlying stock price. The control variables include option and stock characteristics as described in Table 1. Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample period is 1996 to 2017.

	Using historical volatility		Using GARCH(1,1) volatility	
	Calls	Puts	Calls	Puts
Intercept	−1.819	−1.571	−1.183	−1.076
	(−14.53)	(−13.37)	(−14.11)	(−12.34)
Log(stock price)	0.387	0.311	0.417	0.381
	(15.82)	(14.08)	(15.01)	(15.12)
IVOL	2.749	0.581	3.557	3.335
	(3.22)	(0.53)	(4.05)	(4.30)
ISKEW	−0.016	−0.028	−0.005	−0.004
	(−12.97)	(−12.80)	(−2.97)	(−2.28)
IKURT	−0.002	−0.002	0.002	0.002
	(−2.88)	(−2.37)	(4.41)	(5.94)
MAX10	4.163	6.576	2.401	3.145
	(8.00)	(8.31)	(4.49)	(6.57)
Option volume/open interest	0.007	0.008	−0.004	0.000
	(2.96)	(4.42)	(−4.73)	(0.16)
Option bid-ask spread	−0.198	−0.508	0.015	−0.138
	(−5.95)	(−12.57)	(0.37)	(−3.65)
Gamma	1.916	2.214	2.453	2.665
	(10.60)	(11.59)	(10.25)	(9.51)
Vega	−3.471	−1.575	−2.835	−1.976
	(−8.72)	(−7.02)	(−9.00)	(−9.16)
Log(size)	0.007	−0.004	−0.042	−0.048
	(2.16)	(−0.80)	(−9.69)	(−11.45)
Log(market-to-book)	−0.010	0.000	0.022	0.028
	(−3.34)	(−0.01)	(7.04)	(7.37)
Past stock return	−0.044	−0.071	0.026	0.034
	(−5.86)	(−8.02)	(2.93)	(3.66)
Profitability	0.018	0.019	−0.005	−0.004
	(5.53)	(4.99)	(−3.83)	(−2.22)
Forecast dispersion	0.004	0.011	0.000	0.004
	(0.75)	(1.62)	(0.04)	(0.70)
Net equity issuance	0.009	−0.025	0.134	0.139
	(0.88)	(−1.63)	(9.02)	(8.13)
Stock illiquidity	−1.027	0.802	−2.084	−1.908
	(−2.25)	(1.27)	(−5.20)	(−2.75)

Table 6: Delta-hedged option return skewness

We calculate the skewness from the time-series of option portfolio returns and call this portfolio skewness. We also calculate cross-sectional skewness by first computing skewness from the cross-section of option returns in portfolio each month and then taking the time-series average of these skewness measures. We call this measure as cross-sectional skewness. We do these calculations for all options as well as for the ten deciles of Table 2, separately for delta-hedged call and put returns. The sample period is 1996 to 2017.

	Portfolio skewness		Cross-sectional skewness	
	Calls	Puts	Calls	Puts
All options	3.038	3.044	1.561	1.648
Decile 1	1.679	2.175	0.988	1.171
Decile 2	2.431	1.974	1.136	1.186
Decile 3	2.209	2.146	1.326	1.218
Decile 4	2.813	2.922	1.285	1.225
Decile 5	2.508	2.661	1.368	1.204
Decile 6	2.959	2.662	1.377	1.242
Decile 7	2.823	2.976	1.406	1.213
Decile 8	3.034	3.262	1.517	1.346
Decile 9	3.296	2.933	1.563	1.216
Decile 10	3.425	3.363	1.754	1.445

Table 7: Effect of transaction costs

We replicate the portfolio sort of Table 2 while assuming different trading prices along the option's bid-ask spread. For the row "Mid bid-ask spread," we assume that the options are transacted at the midpoint of the bid and ask quotes, i.e., the effective spread is zero (the results from Table 2). The other rows correspond to different assumptions on the ratio of the effective bid-ask spread (ESPR) to the quoted bid-ask spread (QSPR). That is, we assume that we buy the options in the top decile (D10 = high stock prices) at a price higher than the mid bid-ask spread and sell the options in the bottom decile (D1 = low stock price) at a price lower than the mid bid-ask spread. The table reports the mean excess return and 7-factor alpha for the top and bottom deciles and the long/short hedge portfolio. The factors are the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. All alphas are in percent per week and the corresponding t-statistics are in parentheses. The sample period is 1996 to 2017.

	Delta-hedged calls			Delta-hedged puts		
	D1	D10	D10−D1	D1	D10	D10−D1
Panel A: Average return						
Mid bid-ask spread	−0.68	−0.14	0.54	−0.46	−0.12	0.34
	(−9.76)	(−3.17)	(9.66)	(−8.59)	(−2.91)	(7.64)
ESPR/QSPR = 10%	−0.60	−0.14	0.46	−0.41	−0.13	0.28
	(−8.73)	(−3.33)	(8.22)	(−7.62)	(−3.15)	(6.32)
ESPR/QSPR = 25%	−0.50	−0.16	0.35	−0.34	−0.14	0.20
	(−7.37)	(−3.63)	(6.28)	(−6.28)	(−3.44)	(4.47)
ESPR/QSPR = 50%	−0.35	−0.18	0.17	−0.22	−0.16	0.06
	(−5.10)	(−4.12)	(3.04)	(−4.05)	(−3.93)	(1.38)
Panel B: 7-factor alpha						
Mid bid-ask spread	−0.55	−0.06	0.50	−0.37	−0.05	0.32
	(−9.44)	(−1.67)	(8.70)	(−8.17)	(−1.49)	(7.09)
ESPR/QSPR = 10%	−0.48	−0.06	0.41	−0.32	−0.06	0.26
	(−8.24)	(−1.90)	(7.32)	(−6.96)	(−1.79)	(5.79)
ESPR/QSPR = 25%	−0.38	−0.08	0.31	−0.25	−0.07	0.18
	(−6.62)	(−2.29)	(5.43)	(−5.38)	(−2.17)	(3.95)
ESPR/QSPR = 50%	−0.23	−0.10	0.13	−0.13	−0.09	0.04
	(−3.94)	(−2.93)	(2.27)	(−2.74)	(−2.80)	(0.88)

Table 8: Changes in option prices around stock splits

The sample contains 1,914 stock splits over the period 1996 to 2017 with options traded on the stock. For each stock split we pick one option; we first identify the shortest maturity options among all options with at least one-month to maturity, and then pick the option that is closest to at-the-money. Panel A shows statistics of the stock split sample. In Panel B we present the change to the option/stock price ratio around the stock split, calculated as:

$$\text{Post/Pre-split option/stock price ratio} = \frac{\text{Post-split option price/Pre-split option price}}{\text{Post-split stock price/Pre-split stock price}}.$$

We look at a window of one to five days before and after the stock split day. Panel C presents the change to the standardized implied volatility of a firm's options around the stock split. Panel D shows the mean option abnormal return around the stock split, where abnormal return is the return on the option's delta-hedged position minus the return on the equivalent position on the S&P 500 index. Panel E shows regressions of the option abnormal return on the (log of) the split ratio. All price ratios and abnormal returns are winsorized at the top and bottom percentiles.

Panel A. Stock split statistics

# of stock splits = 1,914	Mean	Std	Min	P25	P50	P75	Max
Split ratio	2.21	1.26	2.00	2.00	2.00	2.00	50.00
Pre-split stock price	94.95	103.18	12.06	59.73	79.21	108.38	3476.00
Post-split stock price	42.97	23.24	5.07	28.71	37.88	50.68	361.47

		Window around stock split		
		(−1, +1)	(−3, +3)	(−5, +5)
Panel B: Post/pre-split option/stock price ratio				
Calls	Mean ratio	1.07	1.13	1.14
	t-statistic ($H_0 = 1$)	(8.02)	(8.17)	(6.36)
Puts	Mean ratio	1.06	1.09	1.16
	t-statistic ($H_0 = 1$)	(5.75)	(4.00)	(4.73)
Panel C: Post/pre-split standardized IV ratio				
Calls	Mean ratio	1.10	1.08	1.05
	t-statistic ($H_0 = 1$)	(6.29)	(3.72)	(3.35)
Puts	Mean ratio	1.10	1.06	1.09
	t-statistic ($H_0 = 1$)	(5.32)	(3.56)	(5.06)
Panel D: Mean abnormal returns (in %)				
Calls		0.07	0.18	0.19
		(1.28)	(1.70)	(1.07)
Puts		0.28	0.63	1.30
		(6.01)	(5.55)	(6.25)
Panel E: Regression of option returns				
Calls	Intercept	−0.51	−1.65	−2.52
		(−2.67)	(−4.14)	(−3.97)
	Log(split ratio)	0.76	2.42	3.55
		(3.12)	(4.76)	(4.44)
Puts	Intercept	−0.22	−0.72	−1.72
		(−1.28)	(−1.71)	(−2.33)
	Log(split ratio)	0.65	1.78	3.96
		(3.06)	(3.34)	(4.27)

Table 9: Mini-index options

The table shows comparison of option prices on major stock price indices and their traded mini-indices, specifically, the Nasdaq100 Mini-NDX Index Options (MNX) and the S&P500 Mini-SPX Index Options (XSP). Both mini indices are one tenth of the major indices. Each trading day we match an option on the main index with an option on the mini index based on the expiration date and the adjusted strike price. For each pair of options, we compute the price ratio, which equals:

$$\text{Price ratio} = \frac{\text{Mini-index option price} \times 10}{\text{Main index option price}}.$$

We include only options with moneyness (ratio of index to strike price) between 0.9 and 1.1 and present the results for different days to maturity. All price ratios are winsorized at the top and the bottom percentiles. The t-statistics in parentheses are based on standard errors clustered by expiration day/strike price. The sample period for the Nasdaq100 options is 2000 to 2017 and for the S&P500 options is 2013 to 2017.

		Days to maturity		
		Up to 30	31 to 90	91 to 180
Calls	# paired options	13,671	23,839	25,690
	Price ratio	1.0246	1.0042	0.9996
	t-statistic ($H_0 = 1$)	(11.85)	(6.55)	(−1.05)
Puts	# paired options	16,233	23,170	21,965
	Price ratio	1.0626	1.0056	1.0031
	t-statistic ($H_0 = 1$)	(13.47)	(11.67)	(7.47)

Table 10: Effect of institutional ownership

We add to the Fama and MacBeth (1973) regression in Table 4 interaction terms between the (log of) the underlying stock price and institutional ownership (measured by the sum of all shares held by institutions divided by total shares outstanding). All coefficients are multiplied by 100 and Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample period is 1996 to 2017.

	Delta-hedged calls		Delta-hedged puts	
Intercept	−1.787	−2.901	−1.537	−2.561
	(−7.64)	(−6.18)	(−8.57)	(−5.69)
Log(stock price)	0.469	0.938	0.380	0.795
	(7.78)	(7.89)	(7.68)	(7.47)
Institutional ownership	1.536	0.889	1.515	1.168
	(5.92)	(3.52)	(6.06)	(4.44)
Log(stock price)×Institutional ownership	−0.483	−0.299	−0.433	−0.340
	(−6.72)	(−4.22)	(−6.25)	(−4.71)
IVOL		1.570		0.366
		(0.64)		(0.15)
ISKEW		0.003		0.002
		(0.50)		(0.22)
IKURT		−0.006		−0.004
		(−3.54)		(−2.77)
MAX10		2.080		2.137
		(1.52)		(1.66)
Option volume/open interest		−0.004		0.001
		(−0.48)		(0.13)
Option bid-ask spread		−0.283		−0.173
		(−3.98)		(−2.66)
IV−HV		−0.273		−0.141
		(−3.57)		(−2.10)
Gamma		4.226		3.884
		(6.09)		(6.39)
Vega		−5.464		−2.729
		(−5.24)		(−3.56)
Log(size)		−0.052		−0.050
		(−6.13)		(−5.90)
Log(market-to-book)		−0.028		−0.031
		(−2.14)		(−1.92)
Past stock return		−0.047		−0.069
		(−1.11)		(−1.91)
Profitability		0.022		0.037
		(1.13)		(1.81)
Forecast dispersion		0.013		0.060
		(0.47)		(2.02)
Net equity issuance		−0.033		0.080
		(−0.42)		(1.07)
Stock illiquidity		−8.105		−6.043
		(−4.09)		(−2.30)

Table 11: Fama-MacBeth regressions of retail/professional trading on underlying stock price

Each month we run cross-sectional Fama and MacBeth (1973) regressions of net buy trades. Total net buy is the difference between the total daily buy and sell trade positions (measured by both trading volume and quantity of trades), divided by the total daily trade positions. Retail (professional) net buy is the difference between all retail (professional) daily buy and sell trade positions, divided by all retail (professional) daily trade positions. Retail investors include all types of customer traders, and professional investors include proprietary traders and brokers/dealers. The table also shows results for equivalent measures using position-opening trades only. The main independent variable is the log of the underlying stock price. The control variables include the same set of option and stock characteristics as in Table 4. The table shows only the coefficients on the log(stock price), where Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample includes 46,137 call options and 36,056 put options over the period 2009 to 2017.

	Call options			Put options		
	Total net buy	Retail net buy	Professional net buy	Total net buy	Retail net buy	Professional net buy
Trading volume						
All positions	−0.186	−0.252	0.250	−0.052	−0.085	0.249
	(−4.15)	(−5.38)	(3.01)	(−1.31)	(−2.08)	(3.06)
Opening positions	−0.240	−0.316	0.351	−0.086	−0.129	0.523
	(−4.49)	(−5.72)	(4.02)	(−2.38)	(−3.52)	(2.68)
Quantity of trades						
All positions	−0.185	−0.242	0.255	−0.048	−0.079	0.231
	(−4.25)	(−5.47)	(2.86)	(−1.36)	(−2.21)	(2.75)
Opening positions	−0.230	−0.300	0.359	−0.074	−0.113	0.518
	(−4.76)	(−6.08)	(3.91)	(−2.26)	(−3.28)	(2.65)

Table 12: Fama-MacBeth regressions of option expensiveness on net demand

The table shows Fama and MacBeth (1973) firm-level monthly regressions of the option expensiveness on the net demand of retail investors for the options. Option expensiveness is measured as the difference between the option's implied volatility and the expected volatility derived from the GARCH(1,1) model. Net demand is measured as the difference between buy and sell open interest. We consider three versions of net demand: raw, gamma-weighted, and vega-weighted. All three versions are scaled by shares outstanding. The control variables include the total trading volume of the options on the firm's stock during the month, the return on the firm's stock in the past month, and the past volatility of the stock return, measured by the standard deviation of the daily returns over the past year. We run the regression separately for the top and bottom stock price deciles (decile 1 = lowest stock prices, decile 10 = highest stock prices). All coefficients are multiplied by 100 and Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample period is 2009 to 2017.

	Raw net demand		Gamma-weighted net demand		Vega-weighted net demand	
	Decile 1	Decile 10	Decile 1	Decile 10	Decile 1	Decile 10
Intercept	−2.260	2.980	−2.230	2.610	−2.480	2.860
	(−0.55)	(3.83)	(−0.53)	(3.28)	(−0.60)	(3.89)
Net retail demand investors	0.460	−0.030	2.060	2.310	0.510	0.000
	(7.34)	(−1.18)	(5.10)	(3.04)	(5.35)	(0.56)
Total option trading volume	0.620	0.060	0.660	0.100	0.670	0.070
	(2.24)	(1.29)	(2.41)	(1.82)	(2.33)	(1.60)
Past stock return	−11.570	−7.230	−11.570	−7.180	−11.940	−7.390
	(−1.12)	(−2.72)	(−1.10)	(−2.77)	(−1.22)	(−2.80)
Past stock return volatility	−43.080	−42.790	−43.980	−39.370	−44.160	−40.990
	(−1.76)	(−6.00)	(−1.74)	(−5.12)	(−1.83)	(−5.34)

Table 13: Hedging costs

Each month, we first sort all options into quintiles according to three hedging costs measures: stock bid-ask spread (measured by the average daily bid-ask spread in the previous month), stock illiquidity, and idiosyncratic volatility (as described in Table 1). The options are then further sorted into deciles according to the market price of the underlying stock. The table reports the 7-factor alphas of the high-minus-low stock price portfolio, separately for each hedging cost measure quintile. The factors are the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. All alphas are in percent per week and the corresponding t-statistics are in parentheses. The sample period is 1996 to 2017.

	Q1	Q2	Q3	Q4	Q5
	Panel A: Delta-hedged calls				
Stock bid-ask spread	0.01	0.24	0.20	0.28	0.57
	(0.10)	(3.37)	(2.51)	(4.07)	(7.48)
Stock illiquidity	0.05	0.16	0.13	0.27	0.69
	(0.88)	(2.43)	(1.98)	(3.39)	(8.42)
Idiosyncratic volatility	0.11	0.08	0.17	0.32	0.66
	(2.66)	(1.39)	(2.64)	(3.69)	(6.58)
	Panel B: Delta-hedged puts				
Stock bid-ask spread	−0.07	0.04	0.15	0.09	0.36
	(−0.99)	(0.75)	(2.32)	(1.47)	(4.87)
Stock illiquidity	0.07	0.11	0.09	0.17	0.40
	(1.32)	(1.81)	(1.53)	(2.59)	(5.71)
Idiosyncratic volatility	0.09	0.06	0.04	0.23	0.49
	(2.43)	(1.06)	(0.68)	(3.12)	(5.47)

Internet Appendix to "Cheap Options are Expensive"

IA.1 Robustness

IA.1.1 Alternative measures of option returns

In our main tests, we establish our option positions on the expiration date (the third Friday) in a month and hold them until the next expiration date. The holding period thus spans both the remainder of the current month as well as the period prior to the third Friday in the next month. In order to check the robustness of our results to alternative holding periods we calculate three alternative measures of returns.

First, following Cao and Han (2013), we calculate returns until the end of month. Second, we calculate a weekly return for one-week holding period only. In other words, we still rebalance portfolios monthly but restrict the holding period to one week only. Third, again following Cao and Han, we rebalance portfolios daily by adjusting the stock holding to the updated daily delta. Thus, the dollar gain to the daily rebalanced delta-hedged call position, for example, is given by:

$$\Pi = \max(S_1 - K, 0) - \sum_{d=0}^{D-1} \Delta_{C,d}(S_{d+1} - S_d) \tag{IA.1}$$

where D is the number of trading days between option initiation and option expiration, $\Delta_{C,d}$ is the call delta on day d, and S_d is the stock price on day d (S_0 is the stock price at initiation and $S_D \equiv S_1$ is the stock price at expiration).

We then run the FM regressions of these alternative measures of returns on the logarithm of the underlying stock price and the set of stock and option characteristics as in Section 2.4 of the main paper. We report results from these alternative calculations in Table IA.1. We repeat the baseline results in this table to facilitate comparison. Coefficients on most of the controls have consistent signs across specifications. There are a few exceptions. For example, coefficient on Amihud's stock illiquidity is statistically significant only for portfolios held until maturity.

For our interest, the coefficients on the underlying stock price are positive and statistically significant across all regression models in Table IA.1, demonstrating the robustness of our effect to these alternative specifications. We mentioned earlier that in principle, delta-hedged option returns are invariant to underlying return only for continuously adjusted deltas. In this regard, it is useful to note that the coefficient on log stock price is higher for portfolios with daily adjusted deltas than for portfolios with a single delta at the inception of the portfolio. The coefficients for daily-adjusted deltas are -2.900 for calls and -3.158 for puts versus -2.444 for calls and -1.903 for puts for a single delta. While not conclusive, these results alleviate concerns that our option portfolios are picking up the same effect as has been documented for underlying stock returns.

IA.1.2 Various sample splits

In this section, we redo the portfolio sort tests from Table 2 and FM regressions from Table 4 (referred to as "Baseline results") for different subsamples. These robustness results are presented in Table IA.2.

The first subsample excludes all months with large changes in implied volatility for the market, defined by differences in VIX of more than 5% in absolute value between expiration days. This filter removes about 20% of the sample. It is likely that options have realized high (in absolute value) unexpected returns during such periods of large fluctuations in the VIX that are likely to coincide with periods of market instability. We exclude these months to make sure that our results are not driven by extreme option returns. We find that the delta-hedged call (put) 7-factor alpha in this restricted sample is 0.509% (0.312%), which is very close to the baseline results. The magnitudes of FM coefficients on lagged stock price are also not appreciably affected. If anything, the slope coefficients are slightly higher after excluding the months of large changes in VIX.

The second test splits the sample into expansions and recessions. For our sample period, based on NBER definition, the recession months are March 2001 to November 2001, and December 2007 to June 2009. There is usually enhanced uncertainty in the markets surrounding the recession periods. It is unclear ex-ante whether this uncertainty leads to stronger or weaker mispricing of options. The evidence in Table IA.2 suggests that our results are weaker in recessions. The 7-factor alpha is insignificant for both delta-hedged puts and calls, while the coefficient on the stock price in the FM regressions is statistically significant for both delta-hedged calls and puts. Since the recession months constitute only about 10% of our sample, the power of our statistical tests for this subsample is relatively low. The results on the relation between option returns and stock price remain strong and highly significant in expansions.

The third sample split is for January and the other months. As shown by Reinganum (1983), among others, small stocks tend to outperform in the month of January. The evidence in Table IA.2, however, does not reveal any tangible differences in option returns in January versus non-January months. This is true for both the 7-factor alphas as well as FM coefficients. For instance, the 7-factor alpha for delta-hedged calls is 0.480% and 0.483% in January and non-January months, respectively.

The next sample split is based on the sentiment index of Baker and Wurgler (2006). It is conceivable that investors' behavioral bias towards options with low underlying prices is stronger when the overall sentiment in the markets is high. In fact, Stambaugh, Yu, and Yuan (2012) find that stock anomalies are stronger in periods of high sentiment. Consistent with their results, we also find that both the 7-factor alphas and FM coefficients are generally higher in times of high sentiment. For example, the 7-factor alpha for delta-hedged puts is 0.346% and 0.681% in low and high sentiment months, respectively. Nevertheless, the effect of the underlying stock price on option returns remains highly significant in times of low market sentiment as well.

The next two rows show the effect separately for the months associated with positive and negative S&P 500 return and demonstrate the robustness of our results to this sample split.

Finally, we split the sample into two halves for the early (1996-2006) and late (2007-2017) years of our sample period. We find a much stronger effect of the underlying stock price in the first half of the sample. The delta-hedged call 7-factor alpha is 0.762% over 1996-2006 but only 0.266% over 2007-2017. However, the effect remains highly statistically significant in the second half of the sample as well. This finding is consistent with the option markets becoming more efficient over time and mispricing being gradually arbitraged away. It is also consistent with existing studies that examine option returns. For example, Cao et al. (2017) find that regression coefficients on the variables that predict future option returns generally decline in the second half of their sample.

IA.1.3 Alternative options

We use at-the-money options with one month to maturity in our analysis, as these are the most widely traded options. We explore the robustness of our results to other options. We first choose 10% in-the-money (ITM) or 10% out-of-the-money (OTM) options. Table IA.3 shows that the results are broadly like the baseline results. For example, the 7-factor alpha for delta-hedged OTM calls and puts are 0.415% and 0.248%, respectively (both strongly statistically significant). 7-factor alphas for delta-hedged ITM calls and puts are lower than those for ATM options but remain statistically significant. Since ITM calls are closer to stocks, the fact that ITM delta-hedged call (delta-hedging is supposed to account for mispricing in stocks) is still 0.358% is particularly interesting. The FM coefficients on log of stock price for regressions for delta-hedged ITM and OTM calls and puts are also economically and statistically significant.

We next explore options with two, three, and four months to maturity. We continue to hold these options to the next expiration date (meaning that these options are not held to their maturity but only for about a month). Thus, the dollar gain to the call position, for example, is given by:

$$\Pi = C_1 - C_0 - \Delta_{C,0}(S_1 - S_0), \tag{IA.2}$$

where subscripts 0 and 1 refer to option initiation and next month, respectively. Table IA.3 shows that 7-factor alphas for delta-hedged calls are higher for these longer-term options than those for one-month options. The FM coefficient, though, is similar in magnitude across different maturities of call options.

The results for delta-hedged puts are qualitatively similar. The option returns are similar to baseline results for two months to maturity puts but much weaker for longer maturity puts (albeit still statistically significant for three months to maturity puts). The FM coefficients are statistically significant for all maturity options. However, the estimates for longer maturity options are between 0.115 and 0.159 which is about one-fourth the baseline coefficient estimate of 0.587.

Table IA.1: Alternative measures of option returns

Each month we run cross-sectional Fama and MacBeth (1973) regressions of the delta-hedged weekly option returns. The main independent variable is the log of the underlying stock price. The control variables include option and stock characteristics as described in Table 1. The dependent variable is delta-hedged option returns calculated in four different ways. The first measure is the same as in Tables 2 and 4, where the option is held until maturity. The second measure is the delta-hedged return until the end of the month. The third measure is where the option is held for one week. In all three measures the return is the delta-hedged option gain during the investment period scaled by $(\Delta_C S - C)$ and $(P - \Delta_P S)$ for calls and puts, respectively. The fourth measure is where the delta-hedged position is rebalanced daily by adjusting the stock holding to the updated daily delta. All returns are in weekly terms. All coefficients are multiplied by 100 and Newey and West (1987) corrected t-statistics (with twelve lags) are in parentheses. The sample period is 1996 to 2017.

	Delta-hedged calls				Delta-hedged puts			
	Return to maturity	Return to month end	Return to next week	Daily rebal- ancing	Return to maturity	Return to month end	Return to next week	Daily rebal- ancing
Intercept	−2.444	−4.064	−5.999	−2.900	−1.903	−3.481	−4.713	−3.158
	(−5.98)	(−6.47)	(−7.60)	(−6.72)	(−5.42)	(−8.10)	(−6.79)	(−5.32)
Log(stock price)	0.745	1.232	1.768	0.772	0.587	0.972	1.395	0.790
	(7.51)	(7.78)	(7.62)	(8.20)	(7.19)	(7.97)	(7.38)	(6.22)
IVOL	1.778	−2.853	−6.443	−3.925	0.046	−1.346	−2.328	−3.983
	(0.74)	(−1.00)	(−1.62)	(−3.44)	(0.02)	(−0.47)	(−0.75)	(−1.14)
ISKEW	0.002	−0.002	0.014	−0.021	−0.002	−0.021	−0.005	−0.004
	(0.31)	(−0.21)	(1.03)	(−5.88)	(−0.32)	(−2.12)	(−0.33)	(−0.49)
IKURT	−0.005	−0.004	−0.001	−0.004	−0.004	−0.002	−0.001	−0.003
	(−3.55)	(−2.35)	(−0.33)	(−4.25)	(−2.30)	(−1.01)	(−0.27)	(−1.54)
MAX10	1.799	2.103	2.140	4.501	2.162	2.371	0.851	5.347
	(1.30)	(1.00)	(0.89)	(4.66)	(1.68)	(1.34)	(0.43)	(2.60)
Option volume/	0.000	0.019	−0.005	0.012	0.003	0.015	−0.002	0.026
open interest	(0.05)	(2.13)	(−0.33)	(1.81)	(0.46)	(1.50)	(−0.09)	(1.27)
Option bid-ask spread	−0.276	0.162	−0.382	−0.148	−0.162	0.447	0.097	−0.160
	(−4.01)	(1.70)	(−2.43)	(−3.15)	(−2.72)	(4.45)	(0.52)	(−1.73)
IV−HV	−0.287	−0.797	−1.126	−0.607	−0.156	−0.478	−0.626	−0.174
	(−3.88)	(−7.75)	(−8.26)	(−8.98)	(−2.41)	(−5.66)	(−6.38)	(−1.79)
Gamma	4.096	6.265	9.901	3.600	3.789	5.695	8.421	3.653
	(6.14)	(5.64)	(5.58)	(6.03)	(6.48)	(6.20)	(6.02)	(5.02)
Vega	−6.029	−10.958	−14.852	−7.900	−3.421	−7.143	−10.613	−7.019
	(−5.36)	(−6.05)	(−6.07)	(−5.76)	(−4.34)	(−5.76)	(−5.51)	(−4.36)
Log(size)	−0.043	−0.060	−0.073	−0.011	−0.043	−0.045	−0.069	−0.008
	(−5.00)	(−5.17)	(−4.08)	(−2.02)	(−5.63)	(−3.97)	(−4.27)	(−0.68)
Log(market-to-book)	−0.029	−0.020	−0.020	−0.013	−0.033	−0.032	−0.044	−0.017
	(−2.29)	(−1.40)	(−1.48)	(−1.15)	(−1.96)	(−2.03)	(−2.13)	(−0.90)
Past stock return	−0.051	−0.076	−0.113	−0.015	−0.073	−0.099	−0.136	−0.092
	(−1.17)	(−1.93)	(−1.66)	(−0.65)	(−2.06)	(−2.56)	(−2.54)	(−2.08)
Profitability	0.026	−0.033	−0.048	0.049	0.037	−0.016	−0.047	0.107
	(1.32)	(−1.30)	(−1.22)	(3.69)	(1.90)	(−0.67)	(−1.46)	(3.67)
Forecast dispersion	0.017	0.069	0.074	0.063	0.063	0.083	0.085	0.127
	(0.65)	(1.42)	(1.05)	(2.77)	(2.18)	(2.04)	(1.33)	(2.53)
Net equity issuance	−0.029	0.011	−0.003	0.028	0.064	0.089	−0.025	0.045
	(−0.37)	(0.16)	(−0.03)	(0.66)	(0.85)	(1.04)	(−0.21)	(0.35)
Stock illiquidity	−7.890	0.504	−0.388	−3.052	−7.603	4.800	23.873	−7.924
	(−4.55)	(0.24)	(−0.06)	(−2.48)	(−3.08)	(1.24)	(1.83)	(−1.86)

Table IA.2: Robustness checks for various subsamples

We replicate the portfolio sort results from Table 2 and Fama and MacBeth (1973) regressions from Table 4 (referred to as "Baseline results") for different subsamples. The first subsample excludes all months with large changes in implied volatilities, defined by differences in VIX of more than 5% in absolute value between expiration days (about 20% of the sample). The second subsample includes months during recessions, which according to NBER definition are March 2001 to November 2001 and December 2007 to June 2009. The fourth subsample includes options that mature in January, and the fifth subsamples excludes the month of January. The sixth and seventh subsamples include months with market sentiment below and above the sample median, based on sentiment index of Baker and Wurgler (2006). The eighth and ninth subsamples are periods of negative and positive market returns. The tenth and eleventh subsamples are the early and late years of the full sample period. The table reports only the 7-factor alpha of the long/short high-low stock price portfolio and the mean coefficient of the Log(stock price) from the regressions with the full set of control variables. The full sample period is 1996 to 2017.

	Delta-hedged calls		Delta-hedged puts	
	7-factor alpha	FM regression coefficient	7-factor alpha	FM regression coefficient
Baseline results	0.495	0.745	0.319	0.587
	(8.70)	(7.51)	(7.09)	(7.19)
Excluding large changes in IV	0.509	0.831	0.312	0.669
	(6.94)	(7.04)	(5.30)	(7.28)
Recession	0.067	1.132	0.265	0.913
	(0.19)	(2.77)	(1.05)	(2.34)
Expansion	0.586	0.779	0.363	0.620
	(10.89)	(7.37)	(8.11)	(7.07)
January	0.480	0.978	0.274	0.699
	(2.27)	(2.49)	(1.75)	(2.69)
Non-January	0.483	0.725	0.311	0.578
	(8.20)	(7.36)	(6.61)	(7.05)
Sentiment low	0.346	0.590	0.235	0.464
	(4.80)	(4.54)	(3.88)	(4.03)
Sentiment high	0.681	0.936	0.429	0.739
	(7.65)	(7.23)	(6.38)	(7.87)
Negative market return	0.638	0.805	0.462	0.679
	(5.33)	(4.50)	(4.81)	(5.50)
Positive market return	0.517	0.710	0.293	0.533
	(6.58)	(6.79)	(4.61)	(6.05)
1996-2006	0.762	1.110	0.462	0.845
	(8.39)	(10.85)	(6.25)	(8.06)
2007-2017	0.266	0.378	0.214	0.328
	(4.03)	(7.54)	(3.96)	(6.10)

Table IA.3: Alternative options

We replicate the portfolio sort results from Table 2 and Fama and MacBeth (1973) regressions from Table 4 (referred to as "Baseline results") for different options. In the base case, we use ATM options with one month to maturity. Here we use 10% in-the-money (ITM) and 10% out-of-the-money (OTM) options or options with two, three, and four months to maturity. The rest of the procedure stays the same as in Tables 2 and 4. We report only the 7-factor alpha of the long/short high-low stock price portfolio and the mean coefficient of the log(price) from the regressions with the full set of control variables. The factors are the Fama and French (2015) five factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) zero-beta S&P 500 straddle factor. The sample period is 1996 to 2017.

	Delta-hedged calls		Delta-hedged puts	
	7-factor alpha	FM regression coefficient	7-factor alpha	FM regression coefficient
Baseline results	0.495	0.745	0.319	0.587
	(8.70)	(7.51)	(7.09)	(7.19)
ITM	0.358	0.390	0.168	0.488
	(7.50)	(5.38)	(4.53)	(5.99)
OTM	0.415	1.101	0.248	0.710
	(5.69)	(6.47)	(3.73)	(5.89)
2-month maturity	0.675	0.521	0.215	0.121
	(13.52)	(4.95)	(6.89)	(3.70)
3-month maturity	0.576	0.342	0.067	0.115
	(11.17)	(5.79)	(2.25)	(3.27)
4-month maturity	0.542	0.412	0.059	0.159
	(11.09)	(5.28)	(1.45)	(3.39)