Stock Return Autocorrelations and Expected Option Returns

March 12, 2023

Abstract

We show that the return autocorrelation of underlying stock is an important determinant of expected equity option returns. Using an extended Black-Scholes model incorporating the presence of stock return autocorrelation, we demonstrate that expected returns of both call and put options are increasing in return autocorrelation coefficient of the underlying stock. Consistent with this insight, we find strong empirical support in the cross-section of average returns of equity options. Our paper highlights the necessity to control for stock return autocorrelation when studying option return predictability.

JEL Classification: G11, G12, G13

Keywords: stock return autocorrelation, expected option returns, cross-section of option returns, option portfolios

1 Introduction

Since the seminal work of Black and Scholes (1973), the academic literature on the options market has produced tremendous amount of work in the model specification of stock returns. Studies in this literature typically focus on extending the Black-Scholes model by different ways of relaxing the assumption that stock price follows geometric Brownian motion with constant drift.[1] The focus of the literature has been mainly placed on the pricing of the options contract rather than the returns from option investments.[2] Recent literature has started to pay attention to the determinants of the cross-sectional differences of average equity option returns.[3] However, findings of these papers are often based on market imperfections, and thus do not have direct connections to the rich literature on option pricing models. In this paper, we make an attempt to understand how departures from the traditional assumption of geometric Brownian motion with constant drift as the stock price process can be important determinants of expected option returns. Specifically, we focus on the underlying stock's return autocorrelation and establish both theoretical and empirical relationship between the autocorrelation and expected equity option returns.

In this paper, we build upon the insight from the model studied by Lo and Wang (1995) that incorporates non-zero stock return autocorrelation in the option pricing. Lo and Wang (1995) suggests that investors can misprice an option if they use the unconditional variance in the Black-Scholes formula if returns in fact have non-zero autocorrelation. Different from them, we study how the underlying stock's return autocorrelation can explain the cross section of average equity option returns, rather than option prices. It is not entirely obvious why autocorrelation can be an important determinant of expected option returns. This is

[1]Influential papers in this category include Merton (1976), Heston (1993), Bates (1996), and Duffie, Pan, and Singleton (2000).

[2]Existing literature has mainly focused on the investment problem on index options rather than cross-section of equity options. See, e.g., Liu and Pan (2003) and Faias and Santa-Clara (2017).

[3]Papers along this direction include Goyal and Saretto (2009), Cao and Han (2013), Vasquez (2017), Cao, Vasquez, Xiao, and Zhan (2018), Ruan (2020), Cao, Han, Tong, and Zhan (2021), Bali, Beckmeyer, Moerke, and Weigert (2021).

because while non-zero return autocorrelation implies the drift of the stock price process is not constant, it has no impact on the pricing of options as pointed out by Grundy (1991) and Lo and Wang (1995). Nevertheless, expected future payoffs and hence expected returns of options can be heavily influenced by the non-constant drift of the stock price process. In particular, we show that under the model of Lo and Wang (1995), the expected returns for both calls and puts monotonically increase with the autocorrelation of the underlying stock's return.[4]

The monotonic relationship between the return autocorrelation and expected returns on options is well supported empirically. Using equity option returns data from January 1996 to December 2020, we document the monotonic pattern in quintile portfolio returns sorted by the underlying stock's autocorrelation coefficients. The difference between the highest autocorrelation portfolio and the lowest autocorrelation portfolio delivers a statistically significant monthly return of 3.7% for call options and 6.4% for put options. The results are robust if we look at straddle returns and delta-hedged option returns. We also show that these results are not due to the other known drivers of cross-sectional equity option returns and that they are robust to different portfolio sorting frequencies, different methods to compute autocorrelation, and different moneyness of the option contract. Analyses based on Fama-MacBeth regressions further suggest that our result is not driven by the known determinants of expected equity option returns. Our measure of stock return autocorrelation remains statistically significant after controlling for idiosyncratic volatility from Cao and Han (2013), realized stock return volatility from Hu and Jacobs (2020), variance risk and illiquidity premium from Goyal and Saretto (2009), maximum daily return from Byun and Kim (2016), term structure of implied volatilities from Vasquez (2017), and other stock characteristics studied by Cao et al. (2021).

[4] This is in contrast to Hu and Jacobs (2020) where they find that expected call option return is decreasing in volatility while expected put option return is increasing in volatility. Therefore, our result is unlikely driven by the level of volatility.

We contribute to the theoretical literature on how expected returns of options are determined. Relative to the massive literature on pricing of options, there are few studies that analyzed expected return of options. Under the Black-Scholes model, Rubinstein (1984) derives the expected return of an option over a finite holding period. Coval and Shumway (2001) computes the average returns of zero-beta straddles using index option data, where the betas of the options are computed using the Black-Scholes model. Broadie, Chernov, and Johannes (2009) computes expected hold-to-expiration returns of options under various option pricing models, including the Black-Scholes, the Heston (1993) model, and the stochastic volatility jump model suggested by Bates (1996). Boyer and Vorkink (2014) studies the option portfolio returns sorted by the ex-ante skewness of option returns computed from the Black-Scholes model. Xiao and Vasquez (2016) uses the structural model of firm's capital structure to derive an analytical relationship between the firm's leverage and equity option returns. Also, Hu and Jacobs (2020) uses the Black-Scholes and the Heston model to study the relationship between the underlying stock return volatility and expected option returns. Our contribution is to derive the expected holding period return of options for the class of models in Lo and Wang (1995) which incorporates stock return autocorrelation.

Recent empirical literature has identified some interesting variables that explain the cross-sectional differences of average equity option returns. In particular, several studies have focused on variables that measure the frictions of the underlying stock market and analyzed their impact on the average equity option returns. For instance, Cao and Han (2013) shows the relationship between the underlying stock's idiosyncratic volatility and average delta-hedged equity option returns while Cao, Vasquez, Xiao, and Zhan (2018) and Ruan (2020) document the volatility uncertainty measured by volatility of volatility is related to average delta-hedged equity option returns. In those papers, the cross-sectional differences in average option returns are attributed to market imperfections and financial intermediary constraints. In addition, Cao, Han, Tong, and Zhan (2021) documents interesting findings that many predictors of underlying stock returns can also explain the average delta-hedged equity option returns. Instead of finding variables that capture various aspects of market frictions, our study suggests that an often overlooked attribute of stock return dynamics, namely the autocorrelation, can help to explain the cross-sectional differences of expected option returns.

The remainder of the paper is organized as follows. Section 2 provides the analytical relationship between the stock return autocorrelation and expected option returns building on the models developed in Lo and Wang (1995). Section 3 provides the empirical result using the cross-sectional equity option returns data. Section 4 performs various robustness checks and Section 5 concludes.

2 Stock Return Autocorrelation and Expected Option Returns

2.1 Trending Ornstein-Uhlenbeck Process and Expected Option Returns

Geometric Brownian motion with constant drift has been the standard assumption for stock price process used in option pricing, for example, in the Black-Scholes model. However, this stock price process implies that stock returns have zero autocorrelation. In order to accommodate non-zero autocorrelations in returns, Lo and Wang (1995) considers the following trending Ornstein-Uhlenbeck (O-U) process for log stock price:

$$\mathrm{d}\log(S_t) = (-\gamma[\log(S_t) - \mu t] + \mu)\,\mathrm{d}t + \sigma \mathrm{d}W_t, \tag{1}$$

where S_t is the stock price at time t, μ is the drift coefficient, σ is the diffusion coefficient, $\gamma \geq 0$ is the "speed of adjustment" parameter, and W_t is a standard Weiner process. Unlike the original Black-Scholes model, which assumes that log-prices follow an arithmetic random walk with independently and identically distributed Guassian increments, this log-price process is the sum of a zero-mean stationary autoregressive Gaussian process and a deterministic linear trend.

Defining

$$r_k = \log(S_{t+k}) - \log(S_t) \tag{2}$$

as the k-period continuously compounded return of the underlying stock, it can be readily shown that under the trending O-U process in (1), $r_k \sim N(k\mu, k\sigma_k^2)$, where

$$\sigma_k^2 = \frac{\sigma^2\left(1 - e^{-k\gamma}\right)}{k\gamma}. \tag{3}$$

In addition, the k-period return exhibits a first-lag autocorrelation of

$$\rho_k(1) = -\frac{1}{2}(1 - e^{-k\gamma}), \tag{4}$$

where $\rho_k(1)$ is a monotonic decreasing function of γ.

As noted by Grundy (1991) and Lo and Wang (1995), the risk-neutral dynamics of the stock price remains the same as in the Black-Scholes model even though the stock price follows the trending O-U process under the physical measure. Simple reasoning is that the drift under the risk-neutral measure has to be equal to the risk-free rate r in order to avoid arbitrage. This means that call and put option prices remain the same as in the Black-Scholes model even when the stock price follows the trending O-U process. We denote the corresponding Black-Scholes call and put prices as

$$C_t = C^{BS}(S_t, K, r, \tau, \sigma) = S_t\Phi(d_1) - Ke^{-r\tau}\Phi(d_2), \tag{5}$$

$$P_t = P^{BS}(S_t, K, r, \tau, \sigma) = Ke^{-r\tau}\Phi(-d_2) - S_t\Phi(-d_1), \tag{6}$$

where K is the strike price, r is the continuously compounded risk-free rate, τ is the time-to-maturity,

$$d_1 = \frac{\log\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}}, \tag{7}$$

$$d_2 = d_1 - \sigma\sqrt{\tau}, \tag{8}$$

and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable.

It is important to emphasize that we need to use σ, i.e., the instantaneous volatility in the above formulae to obtain the correct option prices. Using the volatility of r_τ (i.e., σ_τ) in the Black-Scholes formula will lead to erroneous prices for the options. While γ or $\rho_\tau(1)$ has no impact on the price of an option today, it plays an important role in determining the expected future price of an option. In the following Proposition, we present the expected future price of a general European derivative on the underlying stock when the stock price follows the trending O-U process in (1).

Proposition 1. *Suppose the stock price follows the trending O-U process defined in (1). Consider a general European derivative with its payoff at time $t+\tau$ being a deterministic function of the stock price at time $t+\tau$. If the derivative has a current price of*

$$H_t = H_t(S_t, \sigma), \tag{9}$$

then its expected price at $t+k$ for $0 < k \leq \tau$ is given by

$$E_t[H_{t+k}] = e^{rk} H_t(S_t^*, \sigma^*), \tag{10}$$

where[5]

$$S_t^* = S_t \exp\left(\left[\mu - r + \frac{\sigma_k^2}{2}\right] k\right), \tag{11}$$

$$\sigma^{*2} = \frac{k\sigma_k^2 + (\tau - k)\sigma^2}{\tau}. \tag{12}$$

Proofs of all propositions are given in the Appendix. The result of this Proposition is quite general; it covers all kinds of European derivatives, including calls, puts, binary options and compound options. It can also be applied to other types of O-U processes such as bivariate and multivariate O-U processes, which we discuss later in this section. It suggests that as long as one has the ability to compute the derivative price today (either analytically or numerically), one can easily compute its expected price at k periods from now by replacing S_t and σ in the pricing formula with S_t^* and σ^* and then multiplying the price by e^{rk}. It should be noted that Rubinstein (1984) has derived the expected value of the call and put options at times $t+k$ under the assumption that the stock price follows a geometric Brownian motion. His result can be obtained by setting $\sigma_k = \sigma$ and $\tilde{S}_t = S_t \exp((\mu - r)k)$ in Proposition 1.[6]

As a special case of Proposition 1, we can compute the expected payoff of a European derivative at its maturity, and the result is summarized in the following corollary.

Corollary 1.1. *Suppose the stock price follows the trending O-U process defined in (1). For a general European derivative with current price of $H_t = H_t(S_t, \sigma)$ and a time-to-maturity of τ, its expected payoff at maturity is given by*

$$E_t[H_{t+\tau}] = e^{r\tau} H_t(\tilde{S}_t, \sigma_\tau), \tag{13}$$

[5]It should be emphasized that when stock price follows a geometric Brownian motion $\mathrm{d}S_t/S_t = \mu\mathrm{d}t + \sigma\mathrm{d}W_t$, we have $E_t[H_{t+k}] = e^{rk}H_t(S_t^*, \sigma)$ where $S_t^* = S_t\exp((\mu - r)k)$.

[6]Rubinstein's proof relies on direct integration of the Black-Scholes formula to obtain the expected return of the option. It is difficult to generalize his proof to the case of more complex European derivatives.

where

$$\tilde{S}_t = S_t \exp\left(\left[\mu - r + \frac{\sigma_\tau^2}{2}\right]\tau\right). \tag{14}$$

With the ability to compute the expected price of a derivative at any time before maturity, we can compute the expected return of an option for different holding periods, including expected hold-to-expiration return. For the European call and put with time-to-maturity τ, we can use Proposition 1 to obtain their expected k-period ($k \leq \tau$) returns under the trending O-U process as

$$E[R_t^C(k)] = \frac{E_t[C_{t+k}]}{C^{BS}(S_t, K, r, \tau, \sigma)} - 1 = \frac{e^{rk}C^{BS}(S_t^*, K, r, \tau, \sigma^*)}{C^{BS}(S_t, K, r, \tau, \sigma)} - 1, \tag{15}$$

$$E[R_t^P(k)] = \frac{E_t[P_{t+k}]}{P^{BS}(S_t, K, r, \tau, \sigma)} - 1 = \frac{e^{rk}P^{BS}(S_t^*, K, r, \tau, \sigma^*)}{P^{BS}(S_t, K, r, \tau, \sigma)} - 1. \tag{16}$$

With the explicit expressions of $E[R_t^C(k)]$ and $E[R_t^P(k)]$ available, we can analyze the impact of stock return autocorrelation on expected option returns. Note that from (3) and (4), we can see that $\rho_k(1)$ and σ_k are both monotonic decreasing functions of γ, and hence $\rho_k(1)$ is a monotonic increasing function of σ_k^2. As a result, $\partial E[R_t^C(k)]/\partial\rho_k(1)$ has the same sign as $\partial E[R_t^C(k)]/\partial\sigma_k$. Similarly, $\partial E[R_t^P(k)]/\partial\rho_k(1)$ has the same sign as $\partial E[R_t^P(k)]/\partial\sigma_k$. In the following Proposition, we provide explicit expressions of $\partial E[R_t^C(k)]/\partial\sigma_k$ and $\partial E[R_t^P(k)]/\partial\sigma_k$.

Proposition 2. *Suppose the stock price follows the trending O-U process defined in (1). The partial derivatives of $E[R_t^C(k)]$ and $E[R_t^P(k)]$ with respect to σ_k are given by*

$$\frac{\partial E[R_t^C(k)]}{\partial\sigma_k} = \frac{e^{rk}S_t^*k\sigma_k}{C_t}\left[\Phi(d_1^*) + \frac{\phi(d_1^*)}{\sigma^*\sqrt{\tau}}\right], \tag{17}$$

$$\frac{\partial E[R_t^P(k)]}{\partial\sigma_k} = \frac{e^{rk}S_t^*k\sigma_k}{P_t}\left[-\Phi(-d_1^*) + \frac{\phi(d_1^*)}{\sigma^*\sqrt{\tau}}\right], \tag{18}$$

where $\phi(\cdot)$ is the probability density function of a standard normal random variable and

$$d_1^* = \frac{\log\left(\frac{S_t^*}{K}\right) + \left(r + \frac{\sigma^{*2}}{2}\right)\tau}{\sigma^*\sqrt{\tau}}. \tag{19}$$

From (17), we can easily see that $\partial E[R_t^C(k)]/\partial\sigma_k > 0$, so expected return of a call option is an increasing function of the first order autocorrelation of stock returns. For the case of (18), we show in the proof of Proposition 2 that when $k = \tau$ and $\mu > 0$, a sufficient condition for $\partial E[R_t^P(k)]/\partial\sigma_k > 0$ is $K \leq S$ (i.e., the put option is at-the-money or out-of-the-money). In principle, (18) can take negative values when the put is deep in-the-money. However, for reasonable choices of parameters we often encounter, the partial derivative in (18) is positive.

As an example, Figure 1 plots the expected stock return, expected hold-to-expiration returns for at-the-money (ATM) calls, puts and straddles as a function of first-order autocorrelation of stock returns under the trending O-U process, assuming $\mu = 0.1$, $r = 0.05$, $\sigma = 0.2$, and $\tau = 1/12$. The τ-period expected return of the stock is given by $\exp\left(\tau\mu + \frac{\tau\sigma_\tau^2}{2}\right) - 1$. Although σ_τ^2 is an increasing function of the stock return autocorrelation, the impact of stock return autocorrelation on the expected return of the stock is quite minimal, especially for a short horizon like $\tau = 1/12$. In contrast, the expected returns of the ATM calls, puts, and straddles all display a monotonic increasing relation with the stock return autocorrelation coefficient. When we compare the expected option returns between two extreme cases $\rho = 0$, which corresponds to the geometric Brownian motion with constant drift, and $\rho = -0.2$, the difference is 11.28% for call option while it is 11.77% for put options. This suggests that autocorrelation in stock returns indeed has a significant impact on the expected returns of ATM options.

To gain a better understanding of why the autocorrelation of stock return has such a large impact on the expected return of the options, we plot the distribution of $S_{t+\tau}$ for two different cases ($\rho = -0.2$ and 0) in Figure 2, with the current stock price set to $S_t = 1$.

It is obvious that with a higher stock return autocorrelation, there is an increase in the volatility of the stock price at maturity. However, $E[S_{t+\tau}]$ is hardly affected by the increase in volatility because the larger positive outcome of $S_{t+\tau}$ tends to be offset by its larger negative outcome, and the expected stock returns for the two cases are very close to each other (0.969% vs. 1.005%). On the contrary, options benefit from extreme outcomes on only one side and their expected payoffs are heavily affected by the volatility of the stock price at maturity. In Figure 2, we use two vertical lines to indicate the expected payoffs for the stock, conditional on that it is below or above \$1, i.e., $E[S_{t+\tau}|S_{t+\tau} < 1]$ and $E[S_{t+\tau}|S_{t+\tau} > 1]$. For ATM options, these conditional payoffs are the most relevant quantities that determine their expected payoffs. For example, the expected payoff of an ATM call option is equal to

$$E[C_{t+\tau}] = P[S_{t+\tau} > 1](E[S_{t+\tau}|S_{t+\tau} > 1] - 1). \tag{20}$$

When $\rho = -0.2$, the probability for the call to be in the money is 0.5648, and the expected payoff conditional on the call being in the money is $\$1.0455 - \$1 = \$0.0455$. This leads to an expected payoff for the call option to be $0.5648 \times \$0.0455 = \$0.02570$. When $\rho = 0$, the probability for the call to be in the money is 0.5574, and the payoff conditional on it being in the money is $\$1.0512 - \$1 = \$0.0512$. The expected payoff for the call option is $0.5574 \times \$0.0512 = \$0.02854$. Although the difference in the expected payoff for the call options in these two cases is not large (\$0.02570 vs. \$0.02854), the call option is a highly leveraged position and it is selling at a much lower price (\$0.02512) than the stock. As a result, the small difference in the expected payoffs for the call option leads to a large difference of $(0.02854 - 0.02570)/0.02512 = 11.28\%$ for the expected return of the call options. Similar calculation also shows that the expected payoff of ATM put option also increases as the stock return autocorrelation increases from -0.2 to 0. In summary, there are two main reasons why the expected option return is heavily affected by the stock return autocorrelation. One is due to the fact that an option benefits from extreme outcomes because of its asymmetric payoff structure, and the other is the high leveraged position of an option magnifies those extreme outcomes further when returns are considered.

While Figure 1 suggests that autocorrelation of stock return is an important determinant of expected returns of ATM options, it is of interest to understand whether the same pattern continues to hold for options with different levels of moneyness. To this end, we plot expected hold-to-expiration call and put option returns for different levels of moneyness ($K/S = 0.95$, 1, or 1.05). Instead of plotting the expected option return as a function of stock return autocorrelation alone, we plot the expected option return as a function of stock return autocorrelation and stock return volatility. This allows us to judge the relative importance of these two determinants of expected option returns in different scenarios. Figure 3 suggests that stock return autocorrelation is extremely important in determining the expected return of out-of-the-money options (i.e., $K/S = 1.05$ for call and $K/S = 0.95$ for put), especially when the volatility is low. In contrast, for in-the-money options, stock return autocorrelation is an important determinant of their expected returns only when return volatility is high. Hu and Jacobs (2020) suggests that stock return volatility is an important determinant of expected option returns. In particular, they suggest that expected call option return is a decreasing function of stock return volatility whereas the expected put option return is an increasing function of stock return volatility. For the Black-Scholes case (i.e., $\rho = 0$), we indeed observe such a pattern. However, when returns exhibit negative autocorrelation, we find that the expected return of out-of-the-money call option ($K/S = 1.05$) is in fact an increasing function of volatility and the in-the-money put option ($K/S = 1.05$) is a decreasing function of volatility. While we find that stock return volatility is an important determinant of expected option returns across various cases considered in Figure 3, the effect of stock return autocorrelation is just as an important determinant of expected option return as the stock return volatility.

2.2 Generalizations

Although the trending O-U process in 2.1 provides a simple analytical tool to embed autocorrelation of stock returns into the option pricing framework, it has a limitation of being only able to generate negative return autocorrelation. In practice, both negative and positive autocorrelation of stock returns are often observed in the cross-section. To overcome this issue, Lo and Wang (1995) proposes the following bivariate trending O-U process that can generate both negative and positive autocorrelations in stock returns:

$$\mathrm{d}\log(S_t) = (\mu - \gamma[\log(S_t) - \mu t] + \lambda X_t)\,\mathrm{d}t + \sigma \mathrm{d}W_t, \tag{21}$$

$$\mathrm{d}X_t = -\delta X_t \mathrm{d}t + \sigma_x \mathrm{d}W_t^x. \tag{22}$$

where $\delta \geq 0$, $\gamma \geq 0$ and the two Weiner processes W_t and W_t^x are assumed to be independent of each other. For this general case, σ_k^2 and $\rho_k(1)$ have the following expressions

$$\sigma_k^2 = \frac{1}{k\gamma}\left[\sigma^2 + \frac{\lambda^2\sigma_x^2}{\delta(\gamma+\delta)}\right]\left[(1-e^{-k\gamma}) - \frac{\lambda}{\gamma-\delta}\beta_{qx}(e^{-k\delta} - e^{-k\gamma})\right], \tag{23}$$

$$\rho_k(1) = -\frac{(1-e^{-k\gamma})^2 + \frac{\lambda}{\gamma-\delta}\beta_{qx}\left[(1-e^{-k\delta})^2 - (1-e^{-k\gamma})^2\right]}{2\left[1-e^{-k\gamma} - \frac{\lambda}{\gamma-\delta}\beta_{qx}(e^{-k\delta} - e^{-k\gamma})\right]}, \tag{24}$$

where

$$\beta_{qx} = \frac{\gamma\lambda\sigma_x^2}{\delta(\delta+\gamma)\sigma^2 + \lambda^2\sigma_x^2}. \tag{25}$$

With these functional forms, we can prove a similar result to the previous trending O-U case that both σ_k^2 and $\rho_k(1)$ are decreasing function of the "speed of adjustment" parameter γ. As a result, we obtain the same intuition that expected option return is an increasing function of the first-order stock return autocorrelation. The following lemma states this result.

Lemma 2.1. *Under the general bivariate trending O-U process in Equation (21), both σ_k^2 and $\rho_k(1)$ are decreasing functions of γ for fixed δ, λ, σ, and σ_x.*

We provide the proofs in the Appendix. Subsequently, it turns out that for this bivariate O-U process, we can apply Proposition 1 to obtain the expected future price of a European option by simply replacing the expression of σ_k^2 in (3) with the one in (23).

In Figure 4, we plot the expected stock return and expected hold-to-expiration returns for ATM calls, puts, and straddles as a function of autocorrelation coefficient under the bivariate trending O-U process, assuming $\mu = 0.1$, $r = 0.05$, $\sigma = 0.2$, $\tau = 1/12$, $\delta = 0.2$, $\lambda = 2.5$, and $\sigma_x = 0.1$. The expected stock return is largely unaffected by the stock return autocorrelation, but expected returns of ATM calls and puts again show a clear monotonic relationship with the stock return autocorrelation coefficient for the case of the bivariate trending O-U process, similar to the case of the univariate trending O-U process in Figure 1.

We plot in Figure 5 the expected hold-to-expiration returns of calls and puts as a function of stock return autocorrelation and stock return volatility for different levels of moneyness ($K/S = 0.95$, 1, or 1.05) under the bivariate trending O-U process. Similar to Figure 3 which is for the case of the univariate trending O-U process, we find that stock return autocorrelation also has an important impact on expected returns of options under the bivariate trending O-U process, especially for those out-of-the-money options on stocks with low return volatility. In most cases, the stock return autocorrelation is an important determinant of expected option returns, and often more so than the stock return volatility.

The analytical results so far strongly support the positive relationship between the stock return autocorrelation and expected option returns. However, this relationship may depend on the particular choice of model specified in Lo and Wang (1995). The analytical result of Proposition 1 suggests that what really matters for expected option returns is the difference between the holding-period return variance σ_k^2 and the instantaneous return variance σ^2. Therefore, we also consider a less model-dependent approach by looking at the variance ratio statistic studied in Lo and MacKinlay (1988)

$$VR = \frac{\sigma_k^2}{\sigma^2}. \tag{26}$$

We use the return autocorrelation as the main variable of interest throughout the paper. However, we also report the empirical results using variance ratio and discuss its performance relative to the return autocorrelation in Section 4.

Overall, the analytical exercise in this section provides an insight that expected option returns should be an increasing function of the first-order autocorrelation coefficient. In the next section, we test this relationship empirically using equity option return data.

3 Empirical Evidence

3.1 Data and Variable Construction

We collect equity options data including best bid, best offer, implied volatility, expiration date, and strike price from OptionMetrics database. The sample period is from January 1996 to December 2020. For each month, we choose equity options with the moneyness closest to 1 within the range between 0.95 and 1.05, and with time to maturity on the third Friday of next month (i.e., standard monthly option expiration date). The return for each option is computed from its first trading day after the standard monthly option expiration date to its maturity in the following month. This allows us to include the largest portion of equity option trading every month. The reason to choose 30-day ATM equity options is because they are the most actively traded contracts in the equity option market. Following the existing literature, we exclude observations that apparently violate no-arbitrage conditions, have no trading volumes or open interests, have a quoted mid-price less than \$0.125, and have paid cash dividends during the holding period.[7] In our study, we first consider three types of option portfolios: the call option portfolio, the put option portfolio, and the straddle portfolio (i.e., a long position in both call and put options with the same strike price). The returns for each of the three option positions are defined below:

$$R^C_{i,t} = \frac{\max(S_{i,t} - K_i, 0)}{C_{i,t-1}} - 1, \tag{27}$$

$$R^P_{i,t} = \frac{\max(K_i - S_{i,t}, 0)}{P_{i,t-1}} - 1, \tag{28}$$

$$R^{St}_{i,t} = \frac{\max(S_{i,t} - K_i, 0) + \max(K_i - S_{i,t}, 0)}{C_{i,t-1} + P_{i,t-1}} - 1, \tag{29}$$

where i stands for firm i. One problem of using hold-to-expiration option returns is that there are significant portions of options that expire out-of-the-money, leading to a highly skewed return distribution as many of the return observations are equal to -1. The highly skewed distribution may affect the performance of the statistical tests that rely on asymptotic normality (e.g., t-test and Fama-MacBeth regression). Accordingly, following the empirical options literature, we also look at the straddle portfolio which generates a less skewed return distribution (e.g., fewer observations of -1). Another advantage of using straddles is that straddles are less sensitive to the returns of the underlying asset, as well as to the level of volatility as in Hu and Jacobs (2020), therefore being able to reduce the effect of the drift term and the level of volatility. As we have shown in Section 2, since the stock return autocorrelation affects both expected call and put option returns in the same direction, theoretically it should be able to explain expected straddle returns as well.

In addition to raw option returns, we also consider delta-hedged option returns as dependent variables, in order to eliminate that our results are driven by the underlying stock risk premia. By reducing directional risk, delta hedging can also isolate volatility changes for

[7] Note that the equity options are American style that can be exercised early. However, several studies (see, for example, Broadie, Chernov, and Johannes (2007) and Boyer and Vorkink (2014)) argue that adjusting for early exercise has minimal empirical implications. We therefore ignore the possibility of early exercise in our empirical analysis, although our findings are robust to removing this filter.

option traders. We construct the delta-hedged call option portfolio (i.e., a long position in one call and −delta shares of the underlying stock) and the delta-hedged put option portfolio (i.e., a long position in one put and −delta shares of the underlying stock). Following Cao and Han (2013), we construct buy-and-hold delta-hedged option returns as the total dollar gain at the end of the holding period scaled by the absolute value of the total cost to construct the portfolios at the formation date, in order to make it comparable across stocks that may have large differences in market prices. Theoretically, since stock return autocorrelation only affects the terminal option price, the scaling does not change the monotonicity between autocorrelation and option returns.[8] In particular, the delta-hedged call option return is defined as:

$$R_{i,t}^{DC} = \frac{(C_{i,t} - C_{i,t-1}) - \Delta_{i,t-1}^{C}(S_{i,t} - S_{i,t-1}) - R_{f,t}(C_{i,t-1} - \Delta_{i,t-1}^{C} S_{i,t-1})}{|C_{i,t-1} - \Delta_{i,t-1}^{C} S_{i,t-1}|}, \tag{30}$$

where C and S denoting the call option price and the underlying stock price, $R_{f,t}$ denotes the risk-free rate from time $t-1$ to time t, and $\Delta_{i,t}^{C}$ is the Black-Scholes call option delta for firm i at time t. The numerator of (30) represents the total dollar gain at the end of the holding period. If we hold the option to expiration, $C_{i,t} = \max(S_{i,t} - K_i, 0)$. Similarly, delta-hedged put option return for firm i is given by:

$$R_{i,t}^{DP} = \frac{(P_{i,t} - P_{i,t-1}) - \Delta_{i,t-1}^{P}(S_{i,t} - S_{i,t-1}) - R_{f,t}(P_{i,t-1} - \Delta_{i,t-1}^{P} S_{i,t-1})}{|P_{i,t-1} - \Delta_{i,t-1}^{P} S_{i,t-1}|}. \tag{31}$$

The underlying stock variables, such as stock return, stock price, trading volume, shares outstanding, and share code, are collected from the CRSP database. In our sample, we only include common stocks with share code equal to 10 or 11. At the beginning of the option holding period, we use a past 12-month (250 days) rolling window of daily returns to

[8]The mathematical proof is provided in the internet appendix.

estimate the first-order autocorrelation of underlying stock's return as

$$\hat{\rho}_{i,t} = \frac{\sum_{n=0}^{248}(R^S_{i,t-n} - \bar{R}^S_{i,t})(R^S_{i,t-n-1} - \bar{R}^S_{i,t})}{\sum_{n=0}^{249}(R^S_{i,t-n} - \bar{R}^S_{i,t})^2}, \tag{32}$$

where $\bar{R}^S_{i,t} = \frac{1}{250}\sum_{n=0}^{249} R^S_{i,t-n}$. A 12-month rolling window is reasonable since it can mitigate short-term impacts from earnings announcement or major corporate events. The calculated stock return autocorrelation is then used to sort stocks and options to form the corresponding quintile portfolios. In order to show the robustness of our empirical results, we construct several alternative measures of stock return autocorrelation with different rolling windows. The results of the robustness checks are discussed in Section 4. A stock and its associated options are eligible to be included in the sample at a certain month if the stock has more than 130 daily observations during the past 12 months. To eliminate the effect of bid-ask bounce, especially from penny stocks, we also exclude samples with stock prices less than $5.[9]

In addition, we also construct various existing option return predictors in the literature. We compute realized volatility using past 30-days of the underlying stock's daily returns, implied volatility is based on 30-day at-the-money call options, variance risk premium is constructed by taking the difference between the implied volatility of the ATM call option expiring in 30 days and the realized volatility, stock illiquidity is computed as the monthly average of the daily absolute returns divided by daily trading volume following Amihud (2002), idiosyncratic volatility is defined as the standard deviation of the residuals from the Fama-French three factor model using daily observations within each month, implied volatility term structure is constructed by taking the difference between the 90-day and 30-day implied volatility of the ATM call options, Amihud illiquidity is calculated based on Amihud (2002), realized skewness is calculated using the past 22-day daily returns, and

[9]Our results are robust to including stocks with prices less than $5 and other securities with the share code outside 10 and 11.

maximum daily return is computed based on Bali, Cakici, and Whitelaw (2011) and Byun and Kim (2016).

Table 1 about here

Table 1 provides the summary statistics. During our sample period, we observe 1,674 firms on average for each month that has liquid options contracts traded (either calls or puts) and available stock return autocorrelation based on our definition.[10] Panel A reports the average stock return autocorrelation coefficient being slightly negative at −0.012. Within these firms, we see large variations in the stock return autocorrelation that the 25^{th} percentile of the observations is −0.067 while the 75^{th} percentile of the observations is 0.043. Panel A also reports the summary statistics of hold-to-expiration equity option returns in our sample. As we discussed earlier, the option return is often −100% as many options expire out-of-the-money. As options represent highly leveraged position, the positive side is also quite extreme. The 90^{th} percentile for call, put, and straddle are 186.8%, 141.4%, and 98.4%, respectively. The average monthly return of ATM call options is 7.8% while the average monthly return of ATM put options is −11.4%, as stock returns are positive on average.

In Panel B, we also report average cross-sectional correlations among stock return autocorrelation and other existing return predictors, such as past one-month stock return, Amihud illiquidity, realized skewness, maximum daily return, realized volatility, implied volatility, and variance risk premium. We find stock return autocorrelation has low correlations with existing return predictors which are computed similarly using stock returns. For example, stock return autocorrelation has a very low correlation (-0.002) with variance risk premium and a low correlation (0.007) with realized skewness. On the other hand, it has a substantial positive correlation with realized volatility of 0.146 and with implied volatility of 0.158, although the magnitude is still moderate.

[10]The number of observations for stocks is more than that for options in Table 1, because some stocks do not have both ATM calls and puts.

3.2 Portfolio Sorting

At the beginning of each portfolio holding period, we sort all eligible stocks into quintiles based on their stock return autocorrelations. Within each quintile, we compute both equal-weighted and security price-weighted (based on the security price corresponding to each portfolio) returns and then construct a long-short portfolio between top and bottom quintiles for the following cases: call option returns, put option returns, delta-hedged call option returns, delta-hedged put option returns, straddle returns, and stock returns. The reason for including the underlying stock portfolio is to examine whether the explanatory power of the stock return autocorrelation on average option returns comes from its ability to explain the average returns of the underlying stocks. We hold the portfolio until the expiration date of the options and calculate the corresponding holding period returns. Table 2 displays the empirical results.

Table 2 about here

Table 2 confirms the prediction of our Proposition 2 that expected return of an option is increasing in the stock return autocorrelation. For example, the call options with the lowest underlying stock return autocorrelations (Low) underperform those with the highest underlying stock return autocorrelations (High) by 3.7%/month. Similar evidence applies to put options (6.4%/month) and straddles (4.3%/month). As illustrated in Figures 1 and 4, the expected return of a stock is hardly affected by its return autocorrelation. Consistent with this, we do not see significant difference in the average returns between the portfolios of stocks with low and high return autocorrelations. This suggests that the explanatory power of stock return autocorrelation on average option returns is not due to its explanatory power on average returns of their underlying stocks. In addition, the explanatory power of stock return autocorrelation cannot be fully explained by realized volatility. If it is all driven by realized volatility, we should observe opposite effects of stock return autocorrelation on call and put options (Hu and Jacobs (2020)), while in our case, stock return autocorrelation positively explains the average returns of both call and put options. One possibility of the predictive power of stock return autocorrelation may be driven by the underlying stocks' risk premia. In order to reduce this concern, we consider the long-short delta-hedged option portfolio following Cao and Han (2013). The portfolio spreads of all long-short delta-hedged option portfolios are statistically significantly positive, implying that our results are not driven by the underlying stocks' risk premia.

In Table 2 Panel B, we show that our results hold for security price-weighted portfolios assuming we invest equal shares for all firms in each portfolio. In Panel B, for call option, put option, and stock portfolios, the weights are based on the corresponding security prices. For delta-hedged call, delta-hedged put, and straddle portfolios, the weights are based on the initial investment for each firm in the portfolio. The results in Table 2 are robust if we adjust the raw portfolio spread returns to alphas based on the two-factor option model (i.e., stock illiquidity and idiosyncratic volatility) proposed by Cao et al. (2021), and are provided in the internet appendix. It is worth noting that in Table 2, the call option results are less significant than put options. The reason is because stock return autocorrelation is usually positively correlated with realized volatility. Low autocorrelation, which leads to low call option returns, corresponds with low realized volatility, thus leading to high call option returns based on Hu and Jacobs (2020). The mixed effect between autocorrelation and realized volatility may offset the predictive power of autocorrelation in single portfolio sorting, thus leading to a less significant result for call options. Consistent with this explanation, the sorting results for put options are much stronger, because both high autocorrelation and realized volatility lead to high put option returns.

One may have concerns that the stock return autocorrelation captures known risk factors that determine option returns such as: realized volatility (Hu and Jacobs (2020)), variance risk premium (Goyal and Saretto (2009)), liquidity risk (Christoffersen, Goyenko, Jacobs, and Karoui (2018)), or reflects some well-known option mispricings such as idiosyncratic volatility (Cao and Han (2013)), implied volatility term structure (Vasquez (2017)), or other stock characteristics (Cao et al. (2021)). In order to avoid the case that the stock return autocorrelation only captures the existing predictors documented in the literature (either risk or mispricing), we extend our portfolio analysis through double sorting stocks by various characteristics and stock return autocorrelation. We conduct an unconditional double sorting that for each month, we sort stocks based on a certain characteristic and stock return autocorrelation separately into quintiles and determine their corresponding cutoffs for each bin, thus in total twenty-five bins in two dimensions. We then classify a certain stock into each bin in the five by five group matrix, based on the cutoffs of both the sorted characteristic and stock return autocorrelation from two dimensions. We then calculate the portfolio return difference and the corresponding t-statistics between the top and bottom stock return autocorrelation along each quintile of the bin sorted by one of the other characteristics (e.g., idiosyncratic volatility, illiquidity, variance risk premium, etc.). The empirical results are provided in Table 3.

Table 3 about here

Table 3 confirms that the explanatory power of stock return autocorrelation on average return of options cannot be fully explained by existing risk factors or mispricing effects. In most of the bins sorted by the control variables, we continue to see the average call or put option returns to be positively related to stock return autocorrelations, and most of the average option return differences between the high and low stock return autocorrelation quintiles are statistically significant. The results in Table 3 are robust if we adjust the raw returns to alphas based on the two-factor option model proposed by Cao et al. (2021), or if we look at delta-hedged call portfolios, delta-hedged put portfolios, or straddle portfolios. We provide the additional double-sorting results in the internet appendix.

3.3 Fama-MacBeth Regression

The Fama-MacBeth regression proposed by Fama and MacBeth (1973) provides an alternative way to test whether the explanatory power of stock return autocorrelation on average option return is statistically significant after controlling for other variables. For each type of options (call, put, delta-hedged call, delta-hedged put, or straddle), we run the following cross-sectional regressions of their returns on stock return autocorrelation and other control variables, which have been linked to option returns in the literature (e.g., risk premium and existing option mispricing):

$$R_{i,t} = \alpha_t + \beta_t \hat{\rho}_{i,t-1} + \sum_{j=1}^{M} \gamma_t^j X_{i,t-1}^j + \epsilon_{i,t}, \quad i = 1, \ldots, N_t, \tag{33}$$

where $R_{i,t}$ is the return of option i at time t, $\hat{\rho}_{i,t-1}$ is the estimated stock return autocorrelation for stock i at time $t-1$, and $X_{i,t-1}^j$ $(j = 1, \ldots, M)$ are the control variables including those specified in Section 3.2 and other important option predictors suggested by Cao et al. (2021). Since realized volatility and idiosyncratic volatility are highly correlated, we only include realized volatility in the regression to moderate the multicollinearity issue. We also consider averages of the past one-week, past one-month, and past three-month stock returns to control for the momentum effect. In total, we include 25 independent variables to forecast option returns in the Fama-MacBeth regression. To save space, some of the control variables are summarized in one row as "Other Stock Controls" with the detailed variable definitions listed in the internet appendix.

The cross-sectional regression above is run each month with N_t return observations to obtain the coefficients for the independent variables. When running cross-sectional regressions, we standardize all independent variables with mean zero and standard deviation of one. After obtaining the time-series of the coefficients for the independent variables, we conduct the t-test for each coefficient with one-lag correction of Newey and West (1987).

The hypothesis of the t-test is: $H_0 : \beta = 0$ vs. $H_a : \beta \neq 0$. The average of the time-series coefficients and the corresponding t-statistics are reported in Table 4.

Table 4 about here

To save space, we only report multiple regressions on stock return autocorrelation and all other control variables. The univariate regression results are also significant for all types of option returns and are provided in the internet appendix. Table 4 supports our claim that stock return autocorrelation is an important determinant of expected option returns, with the t-ratios associated with the autocorrelation coefficient ranging from 2.39 to 7.36. The multiple regression results in Table 4 are consistent with previous findings in the literature. For example, the stock realized volatility has opposite effects on call and put option returns (Hu and Jacobs (2020)), variance risk premium and liquidity risk premium can strongly predict straddle returns (Goyal and Saretto (2009)), and the term structure of implied volatilities is positively related to straddle returns (Vasquez (2017)). More importantly, the multiple regression results suggest that the stock return autocorrelation effect cannot be explained by any of the previous findings in the literature because both the coefficients and t-ratios associated with the autocorrelation coefficient are not much changed even in the presence of other explanatory variables.

4 Robustness Checks

4.1 Alternative Measures of Return Autocorrelation and Different Sorting Frequency

We conduct several robustness checks for our main results of equal-weighted portfolios reported in Table 2 Panel A. We first look at the robustness of our measure for stock return autocorrelations. Specifically, we construct the stock return autocorrelation through different rolling windows: 130 days and 350 days. We find that our portfolio-sorting results hold in both cases (Table 5 Panel A). As previously discussed in Section 2, the relationship between the stock return autocorrelation and the expected option return may depend on the specific choice of model used to generate non-zero return autocorrelation. Since the expected option return essentially depends on the divergence of σ_k^2 from σ^2, we also consider a more direct measure of this divergence, namely the variance ratio of Lo and MacKinlay (1988). Following Lo and MacKinlay (1988), we construct the variance ratio as the variance of the k-period continuously compounded returns divided by k times the variance of one period continuously compounded returns. Since the target portfolio is held for around a month, we choose $k = 22$ for our empirical analysis. Specifically, the variance ratio (VR) is computed as

$$VR_k = \frac{\hat{\sigma}_k^2}{\hat{\sigma}^2} \tag{34}$$

where

$$\hat{\sigma}^2 = \frac{1}{T-1}\sum_{t=1}^{T}(r_t - \hat{\mu})^2, \tag{35}$$

$$\hat{\sigma_k}^2 = \frac{1}{m}\sum_{t=k}^{T}(r_{t-k+1} + \cdots + r_t - k\hat{\mu})^2, \tag{36}$$

$$m = k(T-k+1)\left(1 - \frac{k}{T}\right), \tag{37}$$

$$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} r_t, \tag{38}$$

where r_t denotes the continuously compounded daily return at time t and T is the number of daily observations. In order to match the maturity of the options in our empirical work, we choose $k = 22$ and compute the variance ratio based on daily returns of the underlying stock over the past 12 months. Lo and MacKinlay (1988) shows that VR_k is approximately a linear combination of the first $k-1$ autocorrelation coefficients. When Lo and Wang (1995) model holds, stock returns follow an AR(1) process. As a result, autocorrelations of all lags are completely determined by the first-lag autocorrelation. In this case, VR_k is simply a noisier measure of the first-lag autocorrelation. However, when Lo and Wang (1995) model does not hold, VR_k may contain additional information that is not captured by the first-lag autocorrelation. Therefore, whether the return autocorrelation or the variance ratio performs better is an empirical question. Panel A of Table 5 reports the result using the variance ratio to sort the option portfolios. We find that the portfolio-sorting performance is slightly weaker than the result obtained using first-lag autocorrelation, indicating VR_k could be a noisier measure of the first-lag autocorrelation. Lastly, since stock return autocorrelation is calculated by dividing autocovariance by the realized variance of stock returns, the predictive power of autocorrelation may be driven by the inverse of stock realized volatility. To reduce this concern, we look at the predictive power of autocovariance as well. We find that the autocovariance is able to forecast option returns, implying that the predictive power of autocorrelation is not fully driven by the inverse of stock realized volatility. The result of autocovariance is displayed in Table 5.

Table 5 about here

Second, we investigate how robust our finding is to different sorting frequencies, in order to better understand how persistent and stable our finding is. If the turnover of the portfolio rebalancing is high (i.e., the probability of stocks staying in the same portfolio next period is low), our findings may not be stable and less profitable for trading in practice after transaction costs. To examine this, we extend sorting frequencies to every 3 months, 6 months, and 12 months, instead of sorting firms every month. In other words, although we still use equity options expiring in 1 month to construct the portfolios, the quintile ranks of the firms only change every 3 months, 6 months, or 12 months. The rest of the calculation follows the same way in Section 3.2. Our empirical evidence shows that the effect of stock return autocorrelation on option returns is very persistent and stable over time. For example, the difference of average put option returns between the highest autocorrelation and the lowest autocorrelation can significantly last for one year (6.4% every month, tantamount to 76.8% each year) by sorting portfolio every 12 months.

4.2 Options with Different Moneyness and Return Calculation

In Section 3, we mainly consider ATM options expiring in one month for our empirical tests. However, based on our theoretical derivation in Section 2, we expect our empirical results should also hold for options with different moneyness and option return calculation, and in particular the stock return autocorrelation effect is expected to be stronger for out-of-the-money (OTM) options. In this subsection, we re-run our empirical tests in Section 3, but use options with alternative moneyness such as OTM and in-the-money (ITM). In addition, the option returns we constructed are mainly from the middle of one month (i.e., the third Friday of the expiration month) to the middle of the next month at expiration. Ni, Pearson, and Poteshman (2005) argues that hold-to-expiration option returns are affected by biases at expiration. To avoid this bias, we follow Cao, Han, Tong, and Zhan (2021) to construct the one-month option returns from the beginning and held to the end of each month. The results are provided in Table 6.

Table 6 about here

We first investigate the explanatory power of stock return autocorrelation for different levels of moneyness. We consider two other types of options: OTM options with moneyness (K/S) less than 0.95 for put options and greater than 1.05 for call options, and ITM options with moneyness less than 0.95 for call options and greater than 1.05 for put options. To exclude those illiquid deep in- or out-of-the money options, we set the lower and upper bounds of moneyness at 0.8 and 1.2. We also construct a portfolio of ITM call and put options as well as a portfolio of OTM call and put options money and report their average returns under the column “Combination”. All the ITM and OTM option returns are computed as the average returns across all available option contracts satisfying the filtering conditions. Consistent with our theoretical results, the positive relation between stock return autocorrelation and average option returns holds for different levels of moneyness. More importantly, the stock return autocorrelation effect is much stronger for OTM call and put options as well as for OTM combination, which is consistent with our model’s prediction. For example, the average monthly quintile spread of OTM put option portfolio is 9.2%, which is larger than the spread (1.8%) of ITM put option portfolio.

Finally, we consider alternative ways of computing option returns. Instead of constructing option returns from the middle of each month, we follow Cao, Han, Tong, and Zhan (2021) and select options at the beginning of each month and choose those options that have a moneyness closest to 1 between 0.9 and 1.1 and with time to maturities between 30 and 55 days. Through this way, the option returns are calculated from the beginning to the end of each month. Since the options are not held to maturity, at the end of the holding period, the option terminal price is calculated as the higher value between the option trading price (equal to zero if unavailable at the selected date) and the exercised option payoff (i.e., intrinsic value) of the option at the particular date. Following Section 4.1, we also examine the portfolio results with different sorting frequencies from 1 month to 12 months. Panel B of Table 6 confirms that our empirical results hold for the alternative definition of option returns.

4.3 Stochastic Volatility

In Section 2, we have assumed the volatility σ to be constant for all models we considered. This is because we are mainly interested in the effect of autocorrelation stemming from the trending drift term and it is analytically convenient to make an assumption of constant volatility. We now relax this assumption by allowing stochastic volatility in the general bivariate trending O-U process to examine if stochastic volatility can substantially alter our conclusions. By embedding Heston (1993) style square-root process of stochastic volatility specification into the general bivariate trending O-U process, we consider the following model of log stock price under the physical measure:

$$\mathrm{d}\log(S_t) = (\mu - \gamma[\log(S_t) - \mu t] + \lambda X_t)\mathrm{d}t + \sqrt{V_t}\mathrm{d}W_t, \tag{39}$$

$$\mathrm{d}X_t = -\delta X_t \mathrm{d}t + \sigma_x \mathrm{d}W_t^x, \tag{40}$$

$$\mathrm{d}V_t = \kappa(\theta - V_t)\mathrm{d}t + \xi\sqrt{V_t}\mathrm{d}W_t^v, \tag{41}$$

where θ is the long-term mean of the variance and κ measures the speed of mean-reversion for the variance. Two Brownian motions W_t and W_t^v are correlated with coefficient ρ while W_t^x is assumed to be independent to others. One of the most attractive feature of Heston (1993) model is being able to generate variance risk premium, which is particularly pronounced in the index options. Therefore, we calibrate the model to the S&P500 index and its options. Using the historical mean of index returns, dividend yield, and risk-free rate, we first set $\mu = 5.86\%$ and $r = 2.25\%$. For the parameters concerning stochastic volatility process, we use parameters estimated in Fournier and Jacobs (2020) and set $\kappa = 5.3178$, $\theta = 0.0408$, $\xi = 0.1882$, $\rho = -0.4694$, $\lambda^{SV} = -1.08$, where λ^{SV} is the standard linear price of variance risk parameter. Under the risk-neutral measure, the joint dynamics are described by the following:

$$\mathrm{d}\log(S_t) = r\mathrm{d}t + \sqrt{V_t}\mathrm{d}W_t^{\mathbb{Q}}, \tag{42}$$

$$\mathrm{d}V_t = \kappa^*(\theta^* - V_t)\mathrm{d}t + \xi\sqrt{V_t}\mathrm{d}W_t^{v,\mathbb{Q}}, \tag{43}$$

where $\kappa^* = \kappa + \lambda_{SV}\xi$ and $\theta^* = \kappa\theta/\kappa^*$.

We rely on simulations to compute the expected option return under this model and plot its relationship with the stock return autocorrelation in Figure 6. Figure 6 demonstrates that our conclusion is not much affected by the inclusion of the stochastic volatility, as monotonic relationship between expected option returns and stock return autocorrelation persists. The major effect coming from the inclusion of the stochastic volatility model is on the decrease in the level of expected option returns through the variance risk premium, but it does not change our main conclusion.

5 Conclusions

This paper presents a new variable that can explain the cross-sectional difference of expected equity option returns, namely the first-order stock return autocorrelation coefficient. Using the extended Black-Scholes framework proposed by Lo and Wang (1995), we show analytically that expected option return is an increasing function of the underlying stock's return autocorrelation. This prediction is strongly supported by the empirical findings where average returns of calls, puts, and straddles are found to be monotonically increasing in the magnitude of their underlying stock's return autocorrelation. These findings are robust to different implementation methods as well as controlling for other known factors that possess explanatory power of cross-sectional differences of average equity option returns.

Our findings contribute to the recent literature on the equity options investment. We identify a new variable that is easy to construct and derive its impact on the cross-section of expected returns on equity options. This approach could be potentially used to study other option pricing models that extends the Black-Scholes formula along different directions although obtaining an analytical formula for expected option return could be challenging for these models. Nevertheless, our results suggest that researchers should take the autocorrelation effect into consideration when they study option-return related predictors. Most importantly, we demonstrate that such analysis could lead to superior investment strategies that offer real benefits for investors even after taking into account of estimation risk and transaction costs.

Appendix

A Proof of Proposition 1

Consider a general European derivative with maturity $t+\tau$ and a payoff at maturity given by

$$H_{t+\tau} = h(S_{t+\tau}), \tag{A.1}$$

where $h(S_{t+\tau})$ is a deterministic function of the underlying stock price at $t+\tau$. As noted in Grundy (1991) and Lo and Wang (1995), the drift of the stock price process is irrelevant for determining the price of the derivative today, and we can use the risk-neutralized process of the stock price to determine the price of the European derivative today. Under the risk neutral measure, the continuously compounded return of $r_{t+\tau} = \log(S_{t+\tau}) - \log(S_t)$ is normally distributed with a mean of $\tau\left(r - \frac{\sigma^2}{2}\right)$ and variance of $\tau\sigma^2$. It follows that the current price of the European derivative is given by

$$\begin{aligned} H_t(S_t, \sigma) &= e^{-r\tau} E_t^{\mathbb{Q}}[h(S_{t+\tau})] \\ &= e^{-r\tau} \int_{-\infty}^{\infty} h\left(S_t e^{(r-\frac{1}{2}\sigma^2)\tau + \sigma\sqrt{\tau}v}\right)\phi(v)\mathrm{d}v. \end{aligned} \tag{A.2}$$

Similarly, the price of the derivative at time $t+k$, where $0 \le k \le \tau$, can be obtained as

$$\begin{aligned} H_{t+k}(S_{t+k}, \sigma) &= e^{-r(\tau-k)} E_{t+k}^{\mathbb{Q}}[h(S_{t+\tau})] \\ &= e^{-r(\tau-k)} \int_{-\infty}^{\infty} h(S_{t+k} e^{(r-\frac{1}{2}\sigma^2)(\tau-k) + \sigma\sqrt{\tau-k}v})\phi(v)\mathrm{d}v. \end{aligned} \tag{A.3}$$

Under the physical measure, the stock price follows a trending O-U process and its k-period continuously compounded return $r_k = \log(S_{t+k}) - \log(S_t)$ is normally distributed with mean $k\mu$ and variance $k\sigma_k^2$. As a result, we can write S_{t+k} as

$$S_{t+k} = S_t e^{\mu k + \sigma_k\sqrt{k}w}, \tag{A.4}$$

where w is a standard normal random variable. Then, we can compute the expected price of the derivative at time $t+k$ as

$$\begin{aligned} E_t[H_{t+k}] &= \int_{-\infty}^{\infty} H_{t+k}\left(S_t e^{\mu k + \sigma_k\sqrt{k}w}, \sigma\right)\phi(w)\mathrm{d}w \\ &= \int_{-\infty}^{\infty}\left[e^{-r(\tau-k)}\int_{-\infty}^{\infty} h\left(S_t e^{\mu k + \sigma_k\sqrt{k}w} e^{(r-\frac{\sigma^2}{2})(\tau-k) + \sigma\sqrt{\tau-k}v}\right)\phi(v)\mathrm{d}v\right]\phi(w)\mathrm{d}w \end{aligned}$$

$$
\begin{aligned}
&= e^{-r(\tau-k)} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h\left(S_t e^{\mu k+(r-\frac{\sigma^2}{2})(\tau-k)} e^{\sqrt{\sigma_k^2 k+\sigma^2(\tau-k)}u}\right)\phi_2\left(u,w;\frac{\sigma_k\sqrt{k}}{\sigma^*\sqrt{\tau}}\right)\mathrm{d}w\mathrm{d}u \\
&= e^{-r(\tau-k)} \int_{-\infty}^{\infty} h\left(S_t e^{\mu k+\left(r-\frac{\sigma^2}{2}\right)(\tau-k)+\sigma^*\sqrt{\tau}u}\right)\phi(u)\mathrm{d}u \\
&= e^{rk} H_t\left(S_t e^{\mu k+\left(r-\frac{\sigma^2}{2}\right)(\tau-k)-\left(r-\frac{\sigma^{*2}}{2}\right)\tau}, \sigma^*\right) \\
&= e^{rk} H_t(S_t^*, \sigma^*),
\end{aligned} \tag{A.5}
$$

where

$$
S_t^* = S_t e^{\mu k+\left(r-\frac{\sigma^2}{2}\right)(\tau-k)-\left(r-\frac{\sigma^{*2}}{2}\right)\tau} = S_t e^{\left(\mu-r+\frac{\sigma_k^2}{2}\right)k} \tag{A.6}
$$

and $\phi_2(\cdot,\cdot;\rho)$ stands for the density function of a standard bivariate normal random variable with correlation ρ. In the above derivation, we make a change of variable of

$$
u = \frac{\sigma_k\sqrt{k}w+\sigma\sqrt{\tau-k}v}{\sqrt{\sigma_k^2 k+\sigma^2(\tau-k)}} = \frac{\sigma_k\sqrt{k}w+\sigma\sqrt{\tau-k}v}{\sigma^*\sqrt{\tau}} \sim N(0,1), \tag{A.7}
$$

and we have

$$
\mathrm{Corr}[u,w] = \mathrm{Cov}[u,w] = \frac{\sigma_k\sqrt{k}}{\sigma^*\sqrt{\tau}}. \tag{A.8}
$$

This completes the proof.

B Proof of Corollary 1.1

This is a special case of Proposition 1 with $k=\tau$, thus $\sigma^*=\sigma_\tau$ and $S_t^* = S_t e^{(\mu-r+\frac{\sigma_\tau^2}{2})\tau} = \tilde{S}_t$. This completes the proof.

C Proof of Proposition 2

From the Black-Scholes formula, it is easy to show that

$$
\frac{\partial C^{BS}(S_t^*,K,r,\tau,\sigma^*)}{\partial S_t^*} = \Phi(d_1^*), \tag{A.9}
$$

$$
\frac{\partial P^{BS}(S_t^*,K,r,\tau,\sigma^*)}{\partial S_t^*} = -\Phi(-d_1^*), \tag{A.10}
$$

$$
\frac{\partial C^{BS}(S_t^*,K,r,\tau,\sigma^*)}{\partial \sigma^*} = S_t^*\phi(d_1^*)\sqrt{\tau}, \tag{A.11}
$$

$$\frac{\partial P^{BS}(S_t^*, K, r, \tau, \sigma^*)}{\partial \sigma^*} = S_t^* \phi(d_1^*)\sqrt{\tau}, \tag{A.12}$$

where

$$d_1^* = \frac{\log\left(\frac{S_t^*}{K}\right) + \left(r + \frac{\sigma^{*2}}{2}\right)\tau}{\sigma^*\sqrt{\tau}}. \tag{A.13}$$

It follows that

$$\begin{aligned}
\frac{\partial E_t[C_{t+k}]}{\partial \sigma_k} &= e^{rk}\left[\frac{\partial C^{BS}(S_t^*, K, r, \tau, \sigma^*)}{\partial S_t^*}\frac{\partial S_t^*}{\partial \sigma_k} + \frac{\partial C^{BS}(S_t^*, K, r, \tau, \sigma^*)}{\partial \sigma^*}\frac{\partial \sigma^*}{\partial \sigma_k}\right] \\
&= e^{rk}\left[\Phi(d_1^*)S_t^* k\sigma_k + S_t^*\phi(d_1^*)\sqrt{\tau}\frac{k\sigma_k}{\tau\sigma^*}\right] \\
&= e^{rk}S_t^* k\sigma_k\left[\Phi(d_1^*) + \frac{\phi(d_1^*)}{\sigma^*\sqrt{\tau}}\right], && \text{(A.14)} \\
\frac{\partial E_t[P_{t+k}]}{\partial \sigma_k} &= e^{rk}\left[\frac{\partial P^{BS}(S_t^*, K, r, \tau, \sigma^*)}{\partial S_t^*}\frac{\partial S_t^*}{\partial \sigma_k} + \frac{\partial P^{BS}(S_t^*, K, r, \tau, \sigma^*)}{\partial \sigma^*}\frac{\partial \sigma^*}{\partial \sigma_k}\right] \\
&= e^{rk}\left[-\Phi(-d_1^*)S_t^* k\sigma_k + S_t^*\phi(d_1^*)\sqrt{\tau}\frac{k\sigma_k}{\tau\sigma^*}\right] \\
&= e^{rk}S_t^* k\sigma_k\left[-\Phi(-d_1^*) + \frac{\phi(d_1^*)}{\sigma^*\sqrt{\tau}}\right]. && \text{(A.15)}
\end{aligned}$$

We now show that when $k = \tau$ and $\mu > 0$, $\partial E_t[P_{t+k}]/\partial \sigma_k > 0$ for at-the-money and out-of-the-money put options. Note that when $k = \tau$ and $\mu > 0$,

$$S_t \geq K \Rightarrow S_t^* \geq K e^{\left(\mu - r + \frac{\sigma_\tau^2}{2}\right)\tau} \Rightarrow d_1^* \geq \sigma^*\sqrt{\tau}. \tag{A.16}$$

It follows that

$$-\Phi(-d_1^*) + \frac{\phi(d_1^*)}{\sigma^*\sqrt{\tau}} \geq -\Phi(-d_1^*) + \frac{\phi(d_1^*)}{d_1^*} = \frac{\Phi(-d_1^*)}{d_1^*}\left[-d_1^* + \frac{\phi(d_1^*)}{\Phi(-d_1^*)}\right] > 0. \tag{A.17}$$

The last inequality follows from the result of Gordon (1941) regarding inverse Mill's ratio for normal random variable that states for $d_1^* \geq 0$,

$$\frac{\phi(d_1^*)}{1 - \Phi(d_1^*)} > d_1^*. \tag{A.18}$$

This completes the proof.

D Proof of Monotonicity of σ_k^2 in γ

We show that under the bivariate O-U process, σ_k^2 is a monotonically decreasing function of γ. The expression of σ_k^2 is given by

$$\sigma_k^2 = \frac{1}{k\gamma}\left[\sigma^2 + \frac{\lambda^2\sigma_x^2}{\delta(\gamma+\delta)}\right]\left[(1-e^{-k\gamma}) - \frac{\lambda}{\gamma-\delta}\beta_{qx}(e^{-k\delta} - e^{-k\gamma})\right], \tag{A.19}$$

where

$$\beta_{qx} = \frac{\gamma\lambda\sigma_x^2}{\delta(\delta+\gamma)\sigma^2 + \lambda^2\sigma_x^2}. \tag{A.20}$$

Taking derivative of σ_k^2 with respect to γ, we obtain

$$\frac{\partial\sigma_k^2}{\partial\gamma} = \frac{e^{-k(\delta+\gamma)}}{\delta\gamma^2(\delta^2-\gamma^2)^2 k}[f_1 + \lambda^2\sigma_x^2 f_2], \tag{A.21}$$

where

$$f_1 = -\delta e^{k\delta}(\delta^2-\gamma^2)^2(e^{k\gamma} - 1 - k\gamma)\sigma^2, \tag{A.22}$$

$$f_2 = 2\gamma^3 e^{k\gamma} - (\delta-\gamma)^2(\delta+2\gamma)e^{k(\delta+\gamma)} + [\delta^2(1+k\gamma) - \gamma^2(3+k\gamma)]\delta e^{k\delta}. \tag{A.23}$$

Since $e^{k\gamma} > 1 + k\gamma$, it is obvious that $f_1 \le 0$. It suffices to show that $f_2 \le 0$. Let $a = k\gamma$ and $b = k\delta$. We can re-write f_2 as a function of a and b as follows

$$\begin{aligned} f_2/k^3 = f(a,b) &= 2a^3e^a - (a-b)^2(b+2a)e^{a+b} + (b^2(1+a) - a^2(3+a))be^b \\ &= 2a^3e^a + b[(1+a)b^2 - (3+a)a^2]e^b - (a-b)^2(2a+b)e^{a+b}. \end{aligned} \tag{A.24}$$

We first show that $f(a, a+d) \le f(a,a) = 0$ for $d > 0$. We have

$$f(a, a+d) = e^a\left\{2a^3 + (a+d)[2a^2(d-1) + d^2 + ad(2+d)]e^d - d^2(3a+d)e^{a+d}\right\}. \tag{A.25}$$

Since $e^a > 0$, it suffices to show that the expression within the braces is non-positive. This follows because

$$\begin{aligned} &2a^3 + (a+d)[2a^2(d-1) + d^2 + ad(2+d)]e^d - d^2(3a+d)e^{a+d} \\ &\le 2a^3 + (a+d)[2a^2(d-1) + d^2 + ad(2+d)]e^d - d^2(3a+d)e^d\left(1 + a + \frac{a^2}{2}\right) \\ &= -\frac{a^2}{2}[d^3e^d + (-4 + 4e^d - 4de^d + 3d^2e^d)a] \end{aligned}$$

$$= -\frac{a^2}{2}\left(d^3e^d + a\sum_{n=2}^{\infty}\frac{3n^2-7n+4}{n!}d^n\right) \leq 0. \tag{A.26}$$

We next show that $f(b+c,b) \leq f(b,b) = 0$ for $c > 0$. We have

$$f(b+c,b) = e^b\left\{b^3(1+b+c) - b(b+c)^2(3+b+c) + 2(b+c)^3e^c - c^2(3b+2c)e^{b+c}\right\}. \tag{A.27}$$

Since $e^b > 0$, it suffices to show that the expression within the braces is non-positive. This follows because

$$\begin{aligned}
&b^3(1+b+c) - b(b+c)^2(3+b+c) + 2(b+c)^3e^c - c^2(3b+2c)e^{b+c} \\
\leq\ &b^3(1+b+c) - b(b+c)^2(3+b+c) + 2(b+c)^3e^c - c^2(3b+2c)e^c\left(1+b+\frac{b^2}{2}\right) \\
\equiv\ &-\frac{b}{2}(d_0 + d_1b + d_2b^2).
\end{aligned} \tag{A.28}$$

Hence, it suffices to show that d_0, d_1, and d_2 are all non-negative. Using power series expansion around 0, we observe that

$$\begin{aligned}
d_0 &= 2c^2[3+c+(2c-3)e^c] = 2c^2\sum_{n=2}^{\infty}\frac{2n-3}{n!}c^n \geq 0, \\
d_1 &= 6c(2+c) + 2c[c(3+c)-6]e^c = 2c\sum_{n=2}^{\infty}\frac{n^2+2n-6}{n!}c^n \geq 0, \\
d_2 &= 4(1+c) + (3c^2-4)e^c = \sum_{n=2}^{\infty}\frac{3n^2-3n-4}{n!}c^n \geq 0.
\end{aligned} \tag{A.29}$$

This completes the proof.

E Proof of Monotonicity of $\rho_k(1)$ in γ

We show that under the bivariate O-U process, $\rho_k(1)$ is a monotonically decreasing function of γ. Given the expression of $\rho_k(1)$, it can be shown that

$$\frac{\partial\rho_k(1)}{\partial\gamma} = \frac{\sigma^4 f_1 + \sigma^2\lambda^2\sigma_x^2 f_2 + \lambda^4\sigma_x^4 f_3}{c}, \tag{A.30}$$

where

$$c = 2e^{k\gamma}\left[e^{k\gamma}(e^{k\delta}-1)\gamma\lambda^2\sigma_x^2 + \delta e^{k\delta}(e^{k\gamma}-1)(\gamma^2\sigma^2 - \lambda^2\sigma_x^2) - \delta^3 e^{k\delta}(e^{k\gamma}-1)\sigma^2\right]^2 > 0 \quad \text{(A.31)}$$

and

$$f_1 = -\delta^2 e^{2k\delta}(e^{k\gamma}-1)^2(\delta^2-\gamma^2)^2 k, \quad \text{(A.32)}$$

$$\begin{aligned} f_2 &= \delta(\delta^2+\gamma^2)e^{k\gamma}(e^{k\delta}-1)(e^{k\gamma}-1)(e^{k\delta}-e^{k\gamma}) \\ &\quad - \delta(\delta^2-\gamma^2)[2k\delta e^{2k\delta}(e^{k\gamma}-1)^2 - k\gamma(e^{k\delta}-1)e^{k\gamma}(e^{k\delta+k\gamma}+e^{k\gamma}-2e^{k\delta})], \end{aligned} \quad \text{(A.33)}$$

$$\begin{aligned} f_3 &= -\delta[e^{k\delta+3k\gamma} - e^{3k\gamma} + k\delta e^{2k\delta}(e^{k\gamma}-1)^2 + (1+k\gamma)e^{2k\gamma} \\ &\quad - (1+k\gamma)e^{2k\delta+2k\gamma} - (1+2k\gamma)(e^{k\delta+k\gamma} - e^{2k\delta+k\gamma})]. \end{aligned} \quad \text{(A.34)}$$

To prove $\partial\rho_k(1)/\partial\gamma \le 0$, we need to prove that $f_1 \le 0$, $f_2 \le 0$, and $f_3 \le 0$. It is obvious that $f_1 \le 0$.

Proof of $f_2 \le 0$:

Let $a = k\gamma$ and $b = k\delta$. Dividing f_2 by δ/k^2, which preserves the sign of f_2, we obtain a function of a and b

$$\begin{aligned} g(a,b) &= (a^2+b^2)e^a(e^a-1)(e^b-1)(e^b-e^a) \\ &\quad + (a^2-b^2)[2be^{2b}(e^a-1)^2 - ae^a(e^b-1)(e^{a+b}+e^a-2e^b)]. \end{aligned} \quad \text{(A.35)}$$

First, consider the case $\delta > \gamma$ so that $b > a$. We want to show that $g(a, a+d) < g(a,a) = 0$ for $d > 0$, hence g is a decreasing function of b for $b > a$ when fixing a. Taking a partial derivative of $g(a, a+d)$ with respect to d, we get $\partial g(a,a+d)/\partial d = -e^{2a}g_1(a,d)$, where

$$\begin{aligned} g_1(a,d) &= -(2a^2+2ad+d^2)e^{a+d}(e^a-1)(e^d-1) - [a^2+(a+d)^2]e^d(e^a-1)(e^{a+d}-1) \\ &\quad - 2(a+d)(e^a-1)(e^d-1)(e^{a+d}-1) \\ &\quad + 2(a+d)[2(a+d)e^{2d}(e^a-1)^2 - a(e^{a+d}-1)(e^{a+d}-2e^d+1)] \\ &\quad + 2d(2a+d)e^d[(1+2d)e^d(e^a-1)^2 + a(e^{2a+d}-2e^{a+d}+2e^d-1)]. \end{aligned} \quad \text{(A.36)}$$

We now show that $g_1(a,d) \ge 0$. Observing that $g_1(0,d) = 0$, it suffices to show that $\frac{\partial g_1}{\partial a} \ge 0$. Repeating similar argument, we have $\frac{\partial g_1}{\partial a}(0,d) = 0$, hence it reduces to showing that $\frac{\partial^2 g_1}{\partial a^2} \ge 0$. We then have

$$\frac{\partial^2 g_1}{\partial a^2}(0,d) = -2d + 8de^d + 4d^2e^d - 6de^{2d} + 6d^2e^{2d} + 8d^3e^{2d}$$

$$= \sum_{n=1}^{\infty} \frac{(n+2)[(2n-3)2^n+4]}{n!} d^{n+1} \geq 0. \tag{A.37}$$

Therefore, it now suffices to show that $\frac{\partial^3 g_1}{\partial a^3}$ is non-negative. We have the following functional form

$$\frac{\partial^3 g_1}{\partial a^3} = 2e^a d_0(a,d) + 2e^a d_1(a,d)a + 8e^{a+d} d_2(a,d)a^2, \tag{A.38}$$

where

$$\begin{aligned} d_0(a,d) &= 4\left(4d^3+19d^2+13d-6\right)e^{a+2d} + 4(d+2)(d+3)e^{a+d} \\ &\quad - \left(4d^3+35d^2+47d-3\right)e^{2d} - d - 3, && \text{(A.39)} \\ d_1(a,d) &= 8\left(5d^2+9d-4\right)e^{a+2d} + 8(d+4)e^{a+d} - \left(10d^2+32d-1\right)e^{2d} - 1, && \text{(A.40)} \\ d_2(a,d) &= (4d-2)e^{a+d} + 2e^a - de^d. && \text{(A.41)} \end{aligned}$$

We now show that d_0, d_1, and d_2 are all non-negative. Since $d_0(a,0) = 0$, taking a derivative with respect to d we obtain

$$\begin{aligned} \frac{\partial d_0}{\partial d} &= 4\left(d^2+7d+11\right)e^{a+d} + 4\left(8d^3+50d^2+64d+1\right)e^{a+2d} \\ &\quad - \left(8d^3+82d^2+164d+41\right)e^{2d} - 1 \\ &\geq 4\left(d^2+7d+11\right)e^{d} + 4\left(8d^3+50d^2+64d+1\right)e^{2d} - \left(8d^3+82d^2+164d+41\right)e^{2d} - 1 \\ &= 4\left(d^2+7d+11\right)e^{d} + \left(24d^3+118d^2+92d-37\right)e^{2d} - 1 \geq 6, && \text{(A.42)} \end{aligned}$$

where the last inequality can be shown by power series expansion in d around 0, which we omit the expression for brevity. Next, since $d_1(a,0) = 0$, taking a derivative with respect to d we obtain

$$\begin{aligned} \frac{\partial d_1}{\partial d} &= 2e^d\left[4\left(10d^2+28d+1\right)e^{a+d} + 4(d+5)e^a - \left(10d^2+42d+15\right)e^d\right] \\ &\geq 2e^d\left[4\left(10d^2+28d+1\right)e^{d} + 4(d+5) - \left(10d^2+42d+15\right)e^d\right] \\ &= 2e^d[4(5+d) + (30d^2+70d-11)e^d] \geq 18e^d, && \text{(A.43)} \end{aligned}$$

where the last inequality can be shown by power series expansion in d around 0, which we omit the expression for brevity. Lastly, since $d_2(a,0) = 0$, taking a derivative with respect to d we obtain

$$\frac{\partial d_2}{\partial d} = e^d[2e^a - 1 + (4e^a - 1)d] > 0. \tag{A.44}$$

This completes the proof that $g(a, a+d) < g(a, a) = 0$ for $d > 0$.

Similarly, we now need to show that $g(b+c, b) < g(b, b) = 0$ for $c > 0$. Taking a partial derivative of $g(b+c, b)$ with respect to c, we get $\partial g(b+c, b)/\partial c = -e^{2b} g_2(b, c)$, where

$$\begin{aligned}
g_2(b,c) = {} & (2b^2 + 2bc + c^2)e^c(e^b - 1)(3e^{b+2c} - 2e^{b+c} - 2e^c + 1) \\
& + 2(b+c)e^c(e^b - 1)(e^c - 1)(e^{b+c} - 1) \\
& - 2(b+c)[2b(e^{b+c} - 1)^2 - (b+c)e^c(e^b - 1)(e^{b+c} + e^c - 2)] \\
& - c(2b+c)e^c\{2b(e^{2b+c} - e^b + e^c - 1) - (e^b - 1)[(2c+1)(e^{b+c} + e^c - 1) - 1]\}.
\end{aligned} \tag{A.45}$$

The proof of $g_2(b, c) \geq 0$ is similar to the proof of $g_1(a, d) \geq 0$, so we only sketch it here. Since $g_2(0, c) = 0$, it suffices to show that $\frac{\partial g_2}{\partial b} \geq 0$. We then show that $\frac{\partial g_2}{\partial b}(0, c) \geq 0$, which suggests that it suffices to show that $\frac{\partial^2 g_2}{\partial b^2} \geq 0$. Repeating similar argument, we have $\frac{\partial^2 g_2}{\partial c^2}(0, c) = 0$ and it suffices to show $\frac{\partial^3 g_2}{\partial b^3} \geq 0$. After simplification, we obtain

$$\frac{\partial^3 g_2}{\partial b^3} = e^{b+c} e_0(b, c) + 2e^{b+c} e_1(b, c) b + 2e^{b+c} e_2(b, c) b^2, \tag{A.46}$$

where

$$\begin{aligned}
e_0(b,c) = {} & 2c^3(8e^{b+c} - 1) + 6(e^c - 1)(16e^{b+c} - 7e^c - 7) + 4c(e^c - 1)(22e^{b+c} - 5e^c - 5) \\
& + c^2(24e^{b+2c} + 32e^{b+c} - 3e^{2c} - 11), \qquad \text{(A.47)} \\
e_1(b,c) = {} & c^2(8e^{b+c} - 1) + (e^c - 1)(80e^{b+c} - 19e^c - 19) \\
& + c(24e^{b+2c} - 56e^{b+c} - 3e^{2c} + 11), \qquad \text{(A.48)} \\
e_2(b,c) = {} & c(2 - 16e^{b+c}) + 3(e^c - 1)(8e^{b+c} - e^c - 1). \qquad \text{(A.49)}
\end{aligned}$$

The proof that e_0, e_1, and e_2 are positive is similar to the proof of of positivity of d_0, d_1, and d_2, so we do not repeat it here. This completes the proof that $g(b+c, b) < 0$, hence $g(a, b)$ is negative for all a and b.

Proof of $f_3 \leq 0$:

We now show that $f_3 \leq 0$. Let $a = k\gamma$ and $b = k\delta$, we need to show that

$$f(a, b) = e^{3a+b} - e^{3a} + be^{2b}(e^a - 1)^2 - (1+a)e^{2a}(e^{2b} - 1) + (1+2a)(e^{a+2b} - e^{a+b}) \geq 0. \tag{A.50}$$

We first show that $f(a, a+d) \geq f(a, a) = 0$ for $d > 0$. We have $f(a, a+d) = e^{2a} g(a, d)$, where

$$g(a,d) = a(e^d - 1)^2 + (e^a - 1)[e^d - 1 - de^{2d} + e^{a+d} + (d-1)e^{a+2d}]. \tag{A.51}$$

As $g(0,d) = 0$, it suffices to show that $\frac{\partial g}{\partial a} \geq 0$. Using the inequality

$$1 + (d-1)e^d = \sum_{n=2}^{\infty} \frac{n-1}{n!} d^n \geq 0, \tag{A.52}$$

we obtain

$$\begin{aligned}
\frac{\partial g}{\partial a} &= (e^a - 1)\{2e^{a+d}[1 + (d-1)e^d] - (e^d - 1)^2\} \\
&\geq (e^a - 1)\{2e^d[1 + (d-1)e^d] - (e^d - 1)^2\} \\
&= (e^a - 1)[-1 + 4e^d + (2d-3)e^{2d}] \\
&= (e^a - 1)\sum_{n=2}^{\infty} \frac{4 + (n-3)2^n}{n!} d^n \geq 0.
\end{aligned} \tag{A.53}$$

We next show that $f(b+c,b) \geq f(b,b) = 0$ for $c > 0$. We have $f(b+c,b) = e^{2b}h(b,c)$, where

$$h(b,c) = b(e^c - 1)^2 + e^c(e^b - 1)[(e^c - 1)(e^{b+c} - 1) - c(-2 + e^c + e^{b+c})]. \tag{A.54}$$

As $h(0,c) = 0$, it suffices to show that $\frac{\partial h}{\partial b} \geq 0$. We have

$$\begin{aligned}
\frac{\partial h}{\partial b} &= (e^{b+c} - 1)[2e^{b+c}(e^c - 1 - c) - (e^c - 1)^2] \\
&\geq (e^{b+c} - 1)[2e^c(e^c - 1 - c) - (e^c - 1)^2] \\
&= (e^{b+c} - 1)(e^{2c} - 2ce^c - 1) \\
&= (e^{b+c} - 1)\sum_{n=2}^{\infty} \frac{2^n - 2n}{n!} c^n \geq 0.
\end{aligned} \tag{A.55}$$

This completes the proof that $f_3 \leq 0$.

References

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5:31–56.

Bali, T. G., H. Beckmeyer, M. Moerke, and F. Weigert. 2021. Option Return Predictability with Machine Learning and Big Data. Working Paper.

Bali, T. G., N. Cakici, and R. F. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of financial economics* 99:427–46.

Bates, D. S. 1996. Jumps and Stochastic Volatility: Exchange Rate Processes Implicit in Deutsche Mark Options. *Review of Financial Studies* 9:69–107.

Black, F., and M. Scholes. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81:637–54.

Boyer, B. H., and K. Vorkink. 2014. Stock Options as Lotteries. *Journal of Finance* 69:1485–527.

Broadie, M., M. Chernov, and M. Johannes. 2007. Model Specification and Risk Premia: Evidence from Futures Options. *Journal of Finance* 62:1453–90.

———. 2009. Understanding Index Option Returns. *Review of Financial Studies* 22:4493–529.

Byun, S.-J., and D.-H. Kim. 2016. Gambling preference and individual equity option returns. *Journal of Financial Economics* 122:155–74.

Cao, J., and B. Han. 2013. Cross Section of Option Returns and Idiosyncratic Stock Volatility. *Journal of Financial Economics* 108:231–49.

Cao, J., B. Han, Q. Tong, and X. Zhan. 2021. Option Return Predictability. *Review of Financial Studies* .

Cao, J., A. Vasquez, X. Xiao, and X. Zhan. 2018. Volatility Uncertainty and the Cross-Section of Option Returns. Working Paper.

Christoffersen, P., R. Goyenko, K. Jacobs, and M. Karoui. 2018. Illiquidity Premia in the Equity Options Market. *Review of Financial Studies* 31:811–51.

Coval, J. D., and T. Shumway. 2001. Expected Option Returns. *Journal of Finance* 56:983–1009.

Duffie, D., J. Pan, and K. Singleton. 2000. Transform Analysis and Asset Pricing for Affine Jump-diffusions. *Econometrica* 68:1343–76.

Faias, J. A., and P. Santa-Clara. 2017. Optimal Option Portfolio Strategies: Deepening the Puzzle of Index Option Mispricing. *Journal of Financial and Quantitative Analysis* 52:277–303.

Fama, E. F., and J. D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81:607–36.

Fournier, M., and K. Jacobs. 2020. A Tractable Framework for Option Pricing with Dynamic Market Maker Inventory and Wealth. *Journal of Financial and Quantitative Analysis* 55:1117–62.

Gordon, R. D. 1941. Values of Mills' Ratio of Area to Bounding Ordinate and of the Normal Probability Integral for Large Values of the Argument. *Annals of Mathematical Statistics* 12:364–6.

Goyal, A., and A. Saretto. 2009. Cross-Section of Option Returns and Volatility. *Journal of Financial Economics* 94:310–26.

Grundy, B. 1991. Option Prices and the Underlying Return's Distribution. *Journal of Finance* 46:1045–69.

Heston, S. 1993. A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options. *Review of Financial Studies* 6:327–43.

Hu, G., and K. Jacobs. 2020. Volatility and Expected Option Returns. *Journal of Financial and Quantitative Analysis* 55:1025–60.

Liu, J., and J. Pan. 2003. Dynamic Derivative Strategies. *Journal of Financial Economics* 69:401–30.

Lo, A. W., and A. C. MacKinlay. 1988. Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test. *Review of Financial Studies* 1:41–66.

Lo, A. W., and J. Wang. 1995. Implementing Option Pricing Models when Asset Returns are Predictable. *Journal of Finance* 50:87–129.

Merton, R. C. 1976. Option Pricing when Underlying Stock Returns are Discontinuous. *Journal of Financial Economics* 3:125–44.

Newey, W. K., and K. D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55:703–8.

Ni, S. X., N. D. Pearson, and A. M. Poteshman. 2005. Stock Price Clustering on Option Expiration Dates. *Journal of Financial Economics* 78:49–87.

Ruan, X. 2020. Volatility-of-volatility and the cross-section of option returns. *Journal of Financial Markets* 48:100492.

Rubinstein, M. 1984. A Simple Formula for the Expected Rate of Return of an Option Over a Finite Holding Period. *Journal of Finance* 39:1503–9.

Vasquez, A. 2017. Equity Volatility Term Structures and the Cross Section of Option Returns. *Journal of Financial and Quantitative Analysis* 52:2727–54.

Xiao, X., and A. Vasquez. 2016. Default Risk and Option Returns. Working Paper.

Table 1
Summary Statistics of Important Variables

Panel A: Stock and Option Characteristics (Monthly Frequency)

			Percentile Values				
Summary Statistics	Avg Obs.	Avg	10th	25th	50th	75th	90th
Return Autocorrelation (ρ)	1,674	−0.012	−0.119	−0.067	−0.012	0.043	0.093
Stock Return (Ret)	1,674	0.011	−0.127	−0.056	0.008	0.073	0.149
Realized Volatility (RV)	1,674	0.446	0.230	0.294	0.398	0.548	0.715
Implied Volatility (IV)	1,674	0.466	0.251	0.317	0.425	0.572	0.728
Variance Risk Premium (VRP)	1,674	0.019	−0.118	−0.040	0.020	0.081	0.161
Call Option Return (CRet)	1,200	0.078	−0.997	−0.944	−0.454	0.597	1.868
Put Option Return (PRet)	1,045	−0.114	−0.971	−0.900	−0.606	0.227	1.414
Straddle Return (StRet)	941	−0.018	−0.859	−0.602	−0.169	0.380	0.984

Panel B: Average Cross-sectional Correlations among Return Predictors

	MOM	ILIQ	Skew	Max	RV	IV	VRP
Return Autocorrelation (ρ)	0.010	−0.009	0.007	0.126	0.146	0.158	−0.002
Past One-month Return (MOM)		0.037	0.423	0.464	0.094	−0.041	−0.188
Amihud Illiquidity (ILIQ)			0.051	0.215	0.206	0.284	0.076
Realized Skewness (Skew)				0.375	0.105	0.038	−0.094
Maximum Daily Return (Max)					0.777	0.594	−0.306
Realized Volatility (RV)						0.703	−0.459
Implied Volatility (IV)							0.289

Panel A provides descriptive statistics for the monthly time-series variables used in the paper. The statistics are calculated by first taking the cross-sectional average of all eligible firm-level observations and then compute the average over time. The variance risk premium is computed as the difference between the annualized 30-day option implied volatility and the annualized 30-day stock realized volatility. A stock and its associated options are eligible to be included in the sample at a certain month if the stock has more than 130 daily observations during the past 12 months. Panel B reports average cross-sectional correlations among autocorrelation and common existing return predictors. Amihud Illiquidity is computed based on Amihud (2002), maximum daily return is computed based on Byun and Kim (2016), and realized skewness is calculated using the past 22-day daily returns for each stock. The sample period is from January 1996 to December 2020.

Table 2
Portfolios Sorted by Stock Return Autocorrelation

Panel A: Equal-weighted Portfolio

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Low	0.050	−0.143	−0.0055	−0.0068	−0.041	0.0107
2	0.076	−0.129	−0.0036	−0.0048	−0.023	0.0114
3	0.090	−0.124	−0.0034	−0.0047	−0.015	0.0117
4	0.084	−0.097	−0.0021	−0.0042	−0.011	0.0113
High	0.088	−0.079	−0.0017	−0.0040	0.002	0.0105
High-Low	0.037	0.064	0.0038	0.0028	0.043	−0.0002
t-stat	(2.60)	(4.61)	(4.07)	(3.46)	(5.72)	(−0.10)

Panel B: Security Price-weighted Portfolio

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Low	0.040	−0.133	−0.0041	−0.0056	−0.045	0.0098
2	0.070	−0.135	−0.0024	−0.0045	−0.028	0.0116
3	0.090	−0.132	−0.0020	−0.0037	−0.017	0.0123
4	0.082	−0.116	−0.0018	−0.0039	−0.018	0.0125
High	0.076	−0.083	−0.0007	−0.0028	−0.001	0.0118
High-Low	0.036	0.051	0.0034	0.0028	0.043	0.0020
t-stat	(2.35)	(3.31)	(4.11)	(3.54)	(4.96)	(1.16)

This table summarizes the average returns in monthly frequencies for portfolios sorted by the stock return autocorrelation and hold for one month. The portfolio securities are specified as the top of each column and are defined in Section 3.1. Panel A reports the equal-weighted average returns, while Panel B reports the security price-weighted average returns assuming we invest equal shares for all firms in the portfolio. In Panel B, for call option, put option, and stock portfolios, the weights are based on the corresponding security prices. For delta-hedged call, delta-hedged put, and straddle, the weights are based on the initial investment for each firm in the portfolio. The sample period is from January 1996 to December 2020.

Table 3
Option Portfolios Double Sorted by Stock Return Autocorrelation and Other Stock Characteristics

Panel A: Double-sorted Call Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.067	0.079	0.059	0.037	0.030
t-stat	(2.91)	(3.40)	(2.80)	(1.61)	(1.20)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.077	0.069	0.069	0.039	0.001
t-stat	(3.23)	(3.13)	(3.18)	(1.72)	(0.03)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.036	0.027	0.057	0.036	0.064
t-stat	(1.59)	(1.21)	(2.51)	(1.54)	(2.94)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.050	0.022	0.032	0.028	0.051
t-stat	(2.24)	(0.97)	(1.38)	(1.27)	(1.96)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.013	0.052	0.035	0.069	0.020
t-stat	(0.56)	(2.35)	(1.53)	(3.22)	(0.85)
Panel B: Double-sorted Put Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.010	0.060	0.060	0.090	0.034
t-stat	(0.40)	(2.92)	(3.16)	(4.06)	(1.50)
Sorted by Idiosyncratic Voaltility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.021	0.042	0.086	0.033	0.067
t-stat	(0.77)	(2.11)	(4.24)	(1.44)	(3.07)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.090	0.054	0.063	0.057	0.067
t-stat	(4.35)	(2.28)	(2.98)	(2.58)	(3.14)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.054	0.091	0.061	0.040	0.081
t-stat	(2.46)	(3.97)	(2.71)	(2.06)	(3.39)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.092	0.061	0.058	0.054	0.060
t-stat	(4.90)	(2.80)	(2.57)	(2.72)	(2.74)

In this table, we conduct an unconditional sorting based on a certain stock characteristic and stock return autocorrelation, in total twenty-five bins in two dimensions. We classify a certain security into each bin based on the cutoffs of the sorted characteristic and stock return autocorrelation. ILIQ stands for the stock illiquidity computed following Amihud (2002) and IVTS denotes the implied volatility term structure defined in Section 3.1. Within each bin we compute the difference of average returns between the high and low stock return autocorrelation quintile. To save space, we only show the results for equal-weighted call and put option portfolios. The results for delta-hedged call, delta-hedged put, and straddle portfolios are provided in the internet appendix. The sample period is from January 1996 to December 2020.

Table 4
Fama-MacBeth Regression

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Intercept	8.268	−13.727	−0.386	−0.538	−2.748	1.284
t-stat	(2.42)	(−2.60)	(−1.99)	(−2.94)	(−1.45)	(3.33)
Autocorrelation	2.675	1.361	0.204	0.153	1.656	0.027
t-stat	(4.85)	(2.39)	(7.36)	(5.23)	(5.68)	(0.62)
Realized Volatility	−7.333	1.960	−0.795	−0.529	−2.596	0.225
t-stat	(−4.34)	(1.02)	(−7.54)	(−4.88)	(−2.41)	(1.07)
Variance Risk Premium	−5.676	1.221	−0.655	−0.421	−2.322	0.098
t-stat	(−5.58)	(0.93)	(−8.37)	(−6.24)	(−3.32)	(0.81)
ILIQ	−1.317	−0.481	−0.102	−0.110	−1.025	0.032
t-stat	(−2.16)	(−0.84)	(−2.59)	(−2.69)	(−2.92)	(0.53)
IVTS	0.874	2.266	0.162	0.134	1.856	0.010
t-stat	(1.22)	(3.10)	(3.46)	(3.13)	(4.69)	(0.15)
Past One-month Return	−2.606	−0.024	−0.187	−0.189	−1.441	−0.016
t-stat	(−2.78)	(−0.02)	(−3.15)	(−2.94)	(−2.63)	(−0.19)
Past Three-month Return	−0.663	−1.337	−0.059	−0.064	−0.726	0.080
t-stat	(−0.73)	(−1.40)	(−1.08)	(−1.15)	(−1.59)	(0.86)
Past One-week Return	−3.043	0.796	−0.128	−0.097	−0.816	−0.180
t-stat	(−4.72)	(1.13)	(−3.11)	(−2.30)	(−2.30)	(−2.69)
Max Daily Return	−1.724	0.051	0.021	−0.028	−0.774	−0.269
t-stat	(−1.46)	(0.04)	(0.26)	(−0.33)	(−1.17)	(−2.09)
Moneyness	0.594	1.129	−0.101	0.067	−0.898	0.081
t-stat	(0.89)	(1.65)	(−3.26)	(2.06)	(−1.57)	(2.60)
Other Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Average adj. R^2 (%)	10.16	11.75	11.98	13.38	10.66	17.23

This table reports the Fama-MacBeth regression for each dependent variable that is the return of different securities specified at the top of each column. The independent variables are stock return autocorrelation and other control variables specified Section 3.3. All predictors are normalized to have mean zero and standard deviation of one at each month. All dependent and independent variables are expressed as monthly values and the coefficients are multiplied by 100. The coefficients in the table are calculated by taking the time-series average of the cross-sectional regressions over time. The t-stat reported is the t-test with Newey-West one-lag correction. The sample period is from January 1996 to December 2020.

Table 5
Robustness Checks for Portfolios Sorted by Stock Return Autocorrelation

Panel A: Alternative Measures of Stock Return Autocorrelation

		Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Autocorrelation (130 days)	High-Low	0.031	0.058	0.0033	0.0025	0.038	0.0008
	t-stat	(2.24)	(4.58)	(4.03)	(3.44)	(5.70)	(0.45)
Autocorrelation (350 days)	High-Low	0.044	0.081	0.0043	0.0033	0.048	−0.0002
	t-stat	(3.00)	(5.89)	(4.58)	(3.97)	(6.82)	(−0.08)
Variance Ratio (250 days)	High-Low	0.021	0.052	0.0028	0.0015	0.029	0.0002
	t-stat	(1.38)	(3.74)	(3.40)	(2.02)	(4.07)	(0.13)
Autocovariancee (250 days)	High-Low	0.023	0.060	0.0048	0.0030	0.031	−0.0028
	t-stat	(1.73)	(5.20)	(4.80)	(3.35)	(4.50)	(−1.64)

Panel B: Alternative Portfolio Sorting Frequency

		Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
3 Months	High-Low	0.035	0.065	0.0042	0.0031	0.044	−0.0006
	t-stat	(2.48)	(5.06)	(4.62)	(3.99)	(6.22)	(−0.32)
6 Months	High-Low	0.030	0.050	0.0031	0.0026	0.038	−0.0008
	t-stat	(2.27)	(3.87)	(3.63)	(3.38)	(5.40)	(−0.51)
12 Months	High-Low	0.014	0.064	0.0027	0.0023	0.032	−0.0020
	t-stat	(1.10)	(4.92)	(3.36)	(2.93)	(4.56)	(−1.32)

This table summarizes robustness checks for the predictive power of stock return autocorrelations. The sorting process is as same as that in Table 2. In Panel A, we first construct four alternative measures for stock return autocorrelation: autocorrelation using 130-day rolling window, autocorrelation using 350-day rolling window, variance ratio of 22 days over 1 day using 250-day rolling window, and autocovariance using 250-day rolling window. In Panel B, similar to Table 2, we keep constructing the portfolios using equity options expiring in 1 month, but sort the portfolio every 3, 6, or 12 months respectively. The corresponding portfolio returns are calculated as the average of monthly option returns with a monthly rollover of the options. All variables in this table are expressed as monthly values, and all portfolios are equally weighted. The sample period is from January 1996 to December 2020.

Table 6
Portfolio Returns Using Different Option Maturity and Moneyness

		Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Panel A: Options with Different Moneyness							
OTM	High-Low	0.079	0.092	0.0059	0.0030	0.029	−0.0002
	t-stat	(3.10)	(2.99)	(4.15)	(2.02)	(3.82)	(−0.10)
ITM	High-Low	0.003	0.018	0.0012	0.0005	0.008	−0.0002
	t-stast	(0.30)	(2.07)	(1.78)	(1.00)	(1.04)	(−0.10)
Panel B: Alternative Option Return Calculation (Month-end to Month-end)							
		Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
1 Month	High-Low	0.036	0.060	0.0054	0.0029	0.036	0.0012
	t-stat	(3.22)	(5.93)	(5.80)	(3.71)	(5.88)	(0.64)
3 Months	High-Low	0.025	0.064	0.0053	0.0031	0.036	−0.0011
	t-stast	(2.23)	(6.49)	(5.94)	(3.90)	(5.98)	(−0.59)
6 Months	High-Low	0.029	0.057	0.0046	0.0027	0.034	−0.0011
	t-stat	(2.75)	(5.61)	(5.54)	(3.45)	(5.91)	(−0.63)
12 Months	High-Low	0.015	0.054	0.0038	0.0025	0.032	−0.0019
	t-stat	(1.54)	(5.55)	(5.05)	(3.65)	(5.66)	(−1.23)

This table reports the robustness checks using alternative types of options. In Panel A, instead of using ATM options, we use options with different moneyness such as out-of-the-money (OTM) options with moneyness less than 0.95 for put options and greater than 1.05 for call options, and in-the-money (ITM) options with moneyness less than 0.95 for call options and greater than 1.05 for put options. The moneyness is defined as the strike price divided by the underlying stock price. To exclude those illiquid deep in- or out-of-the money options, we set the lower and upper bounds of moneyness at 0.8 and 1.2. All the ITM and OTM option returns are computed as the average returns across all available option contracts satisfying the filtering conditions.The call and put combination is the portfolio consisting of both call and put options with the same moneyness. In Panel B, we consider alternative ways of computing options returns. Instead of constructing the option returns from the middle of each month, we use options at the beginning of each month and choose those ATM options (i.e., cloesest to 1 between 0.9 and 1.1) with time to maturities between 30 and 55 days. We then hold it to the end of each month. The sample period is from January 1996 to December 2020.

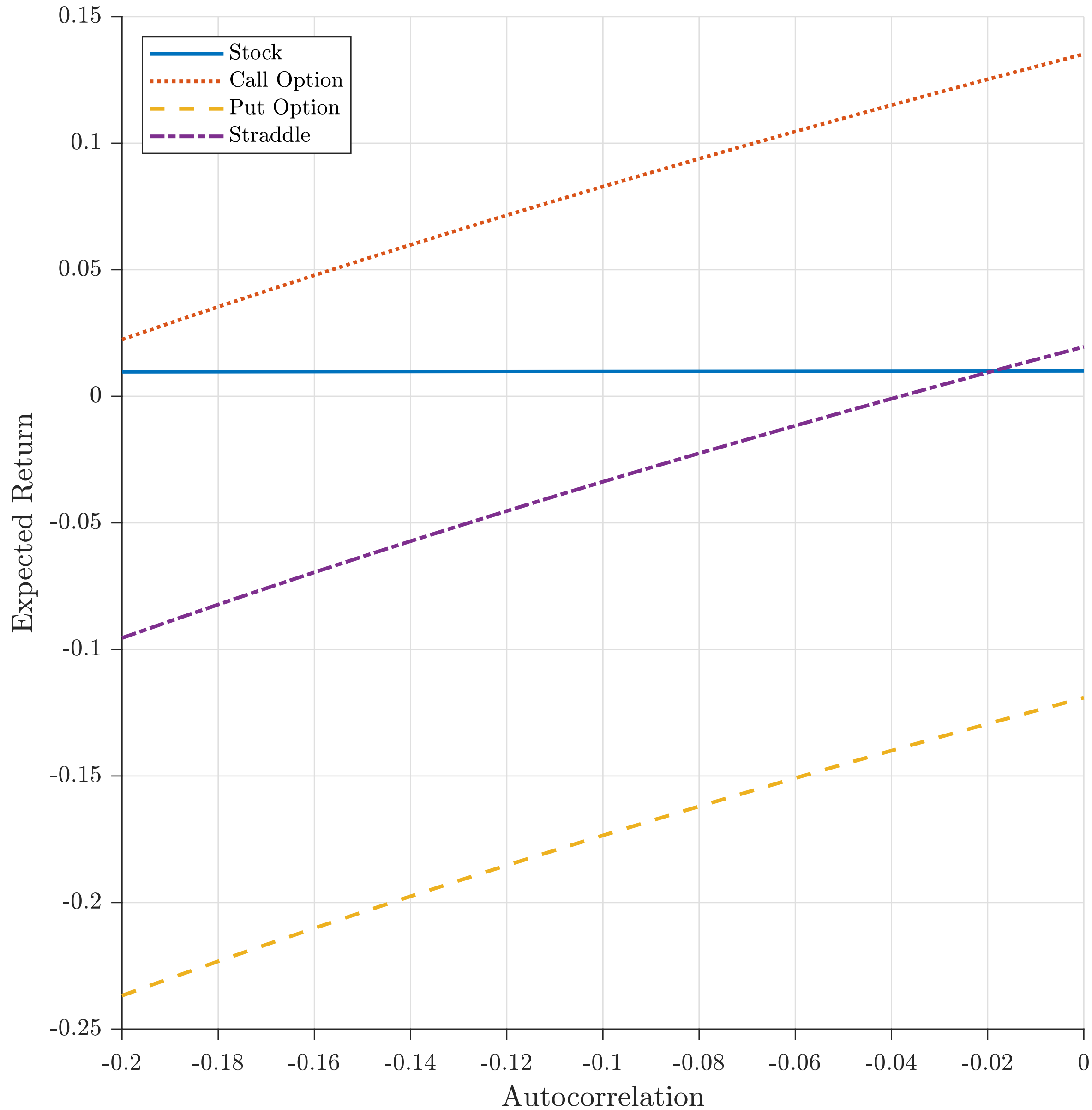

Figure 1
Expected Stock and Option Returns under the Trending O-U Process
This figure plots the expected stock return, expected hold-to-expiration option and straddle returns as functions of first-order autocorrelation of stock returns under the trending O-U process. All options are at-the-money options with the following parameters: $\mu = 0.10$, $r = 0.05$, $\tau = 1/12$, and $\sigma = 0.2$.

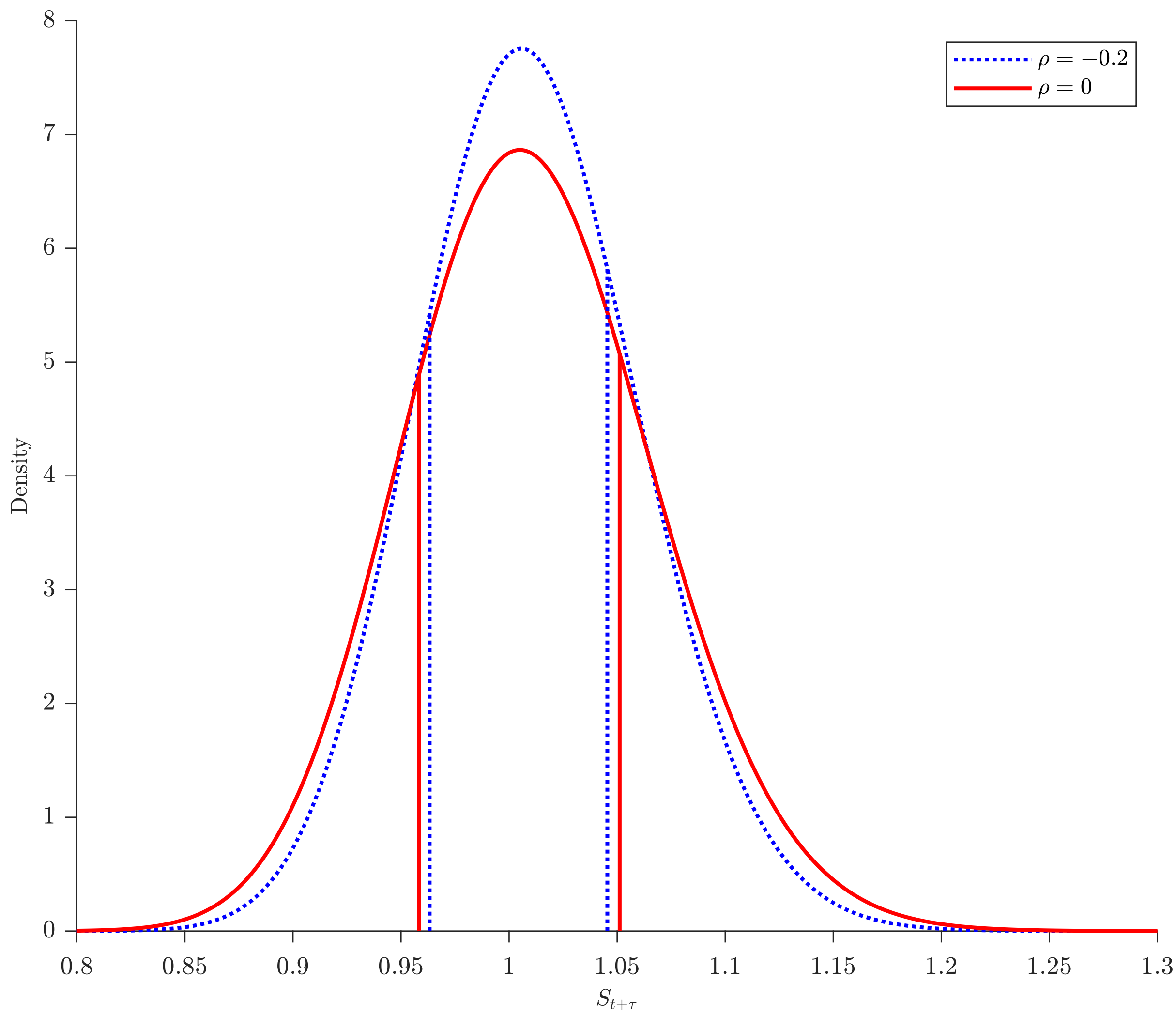

Figure 2
Distribution of Maturity Stock Price under Two Different Trending O-U Processes

This figure plots the distribution of the maturity stock price ($S_{t+\tau}$) for $\tau = 1/12$ under the trending O-U process with parameters $\mu = 0.10$ and $\sigma = 0.2$, when the current stock price (S_t) is normalized to one. The plot shows the distribution of $S_{t+\tau}$ when the first-order autocorrelation of stock returns (ρ) is equal to 0 (solid line) or -0.25 (dotted line). In addition, the vertical lines show the conditional payoff of the stock at maturity when it is above and below the current stock price.

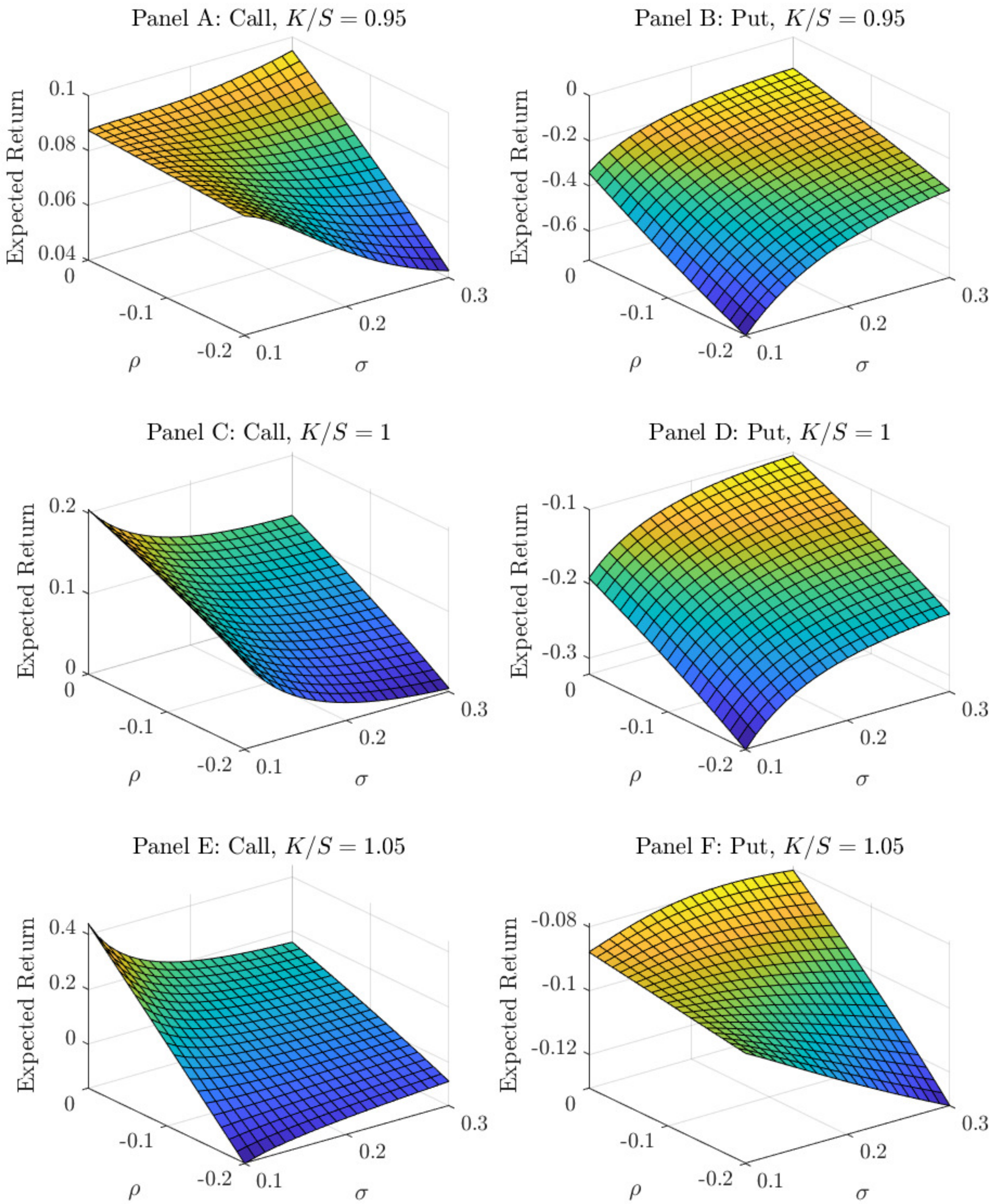

Figure 3
Expected Option Returns under the Trending O-U Process for Different Moneyness

This figure plots the expected hold-to-expiration call and put option returns as functions of volatility (σ) and first-order autocorrelation of stock returns (ρ) under the trending O-U process for three different levels of moneyness and with the following parameters: $\mu = 0.10$, $r = 0.05$, and $\tau = 1/12$.

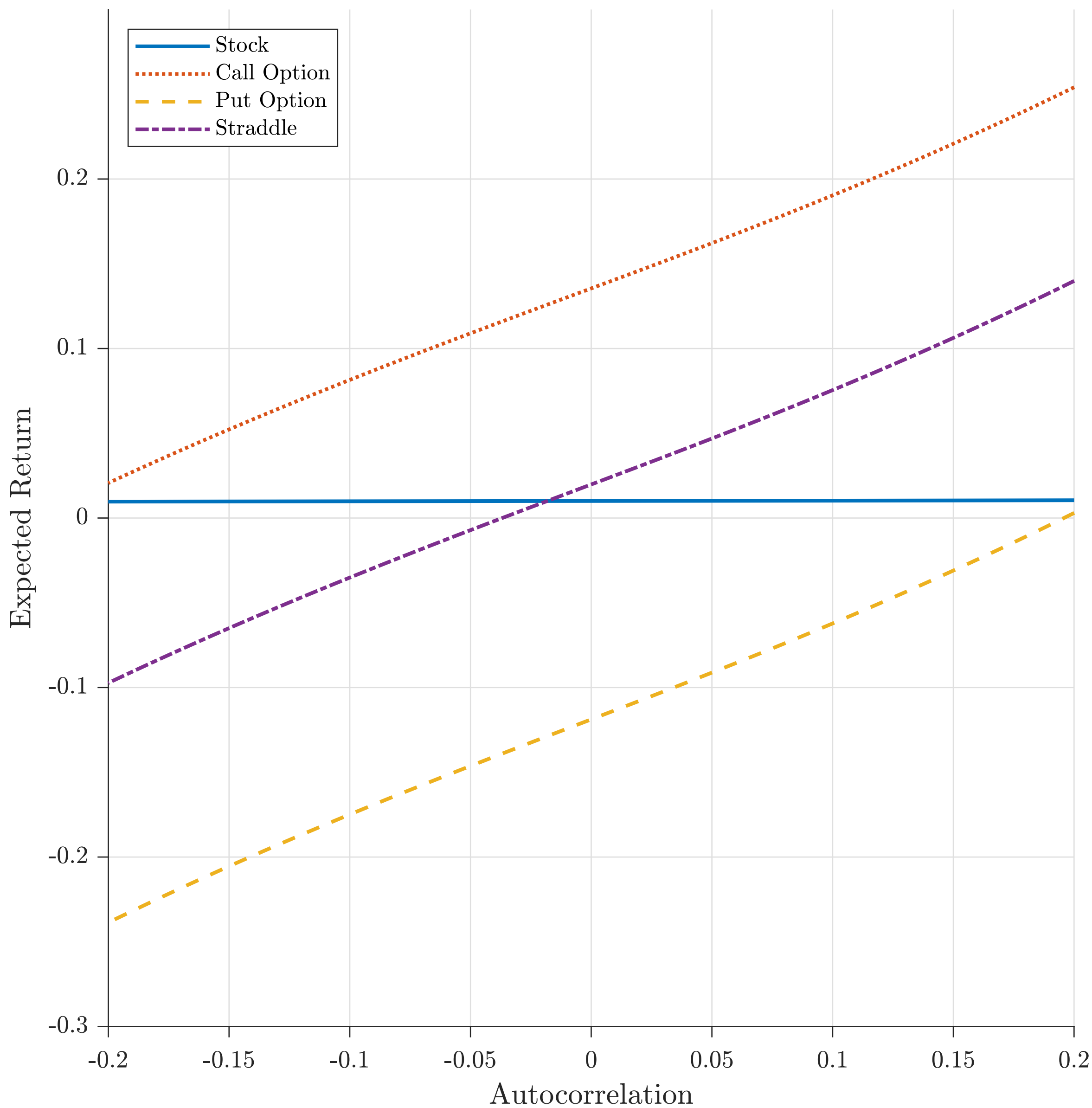

Figure 4
Expected Stock and Option Returns under the Bivariate Trending O-U Process
This figure plots the expected stock return, expected hold-to-expiration option and straddle returns as functions of first-order autocorrelation of stock returns under the bivariate trending O-U process. All options are at-the-money options with the following parameters: $\mu = 0.10$, $r = 0.05$, $\tau = 1/12$, $\sigma = 0.2$, $\sigma_x = 0.1$, $\lambda = 2.5$, and $\delta = 0.2$.

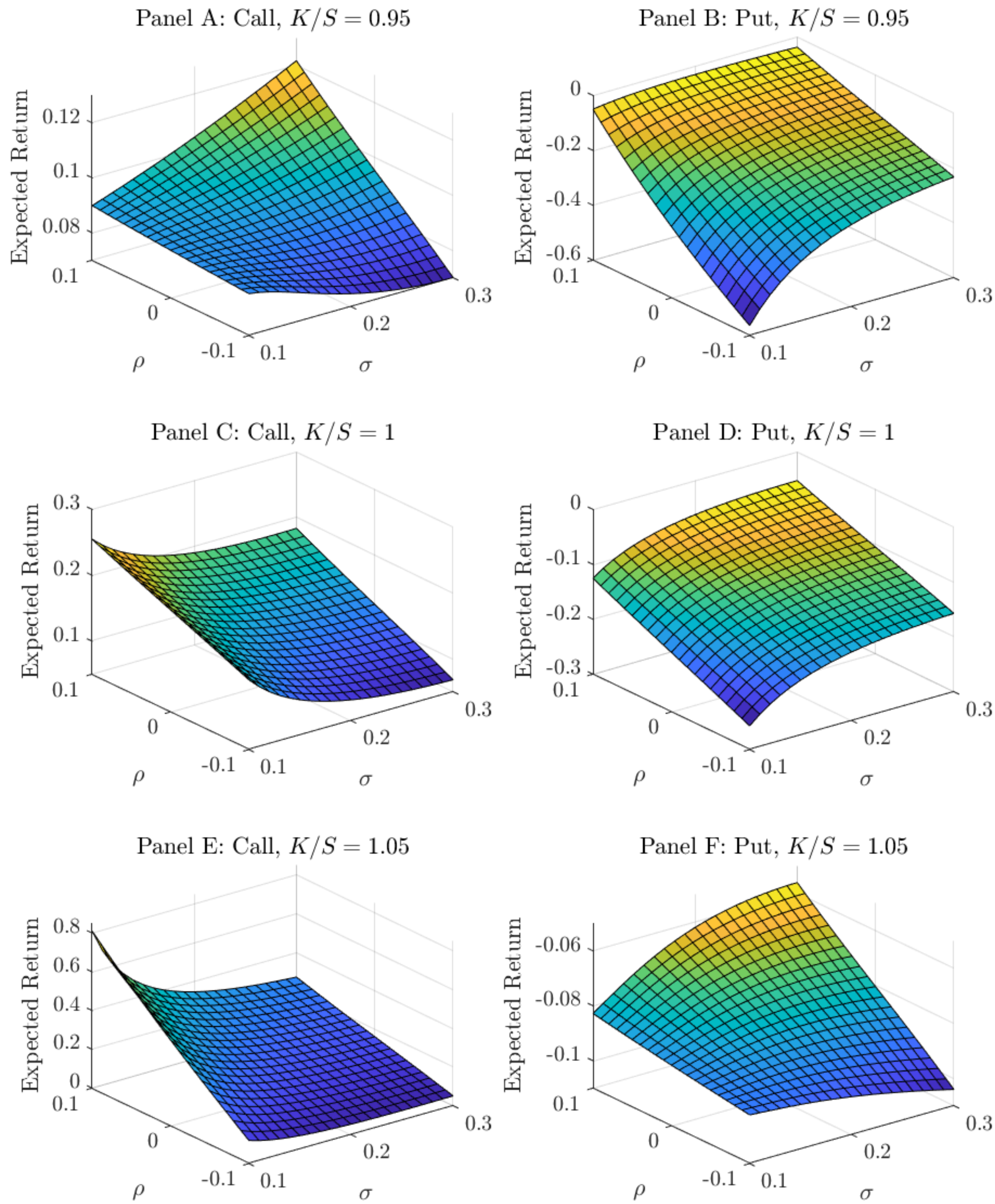

Figure 5
Expected Option Returns under the Bivariate Trending O-U Process for Different Moneyness

This figure plots the expected hold-to-expiration call and put option returns as functions of volatility (σ) and first-order autocorrelation of stock returns (ρ) under the bivariate trending O-U process for three different levels of moneyness and with the following parameters: $\mu = 0.10$, $r = 0.05$, $\tau = 1/12$, $\sigma_x = 0.1$, $\lambda = 2.5$, and $\delta = 0.2$.

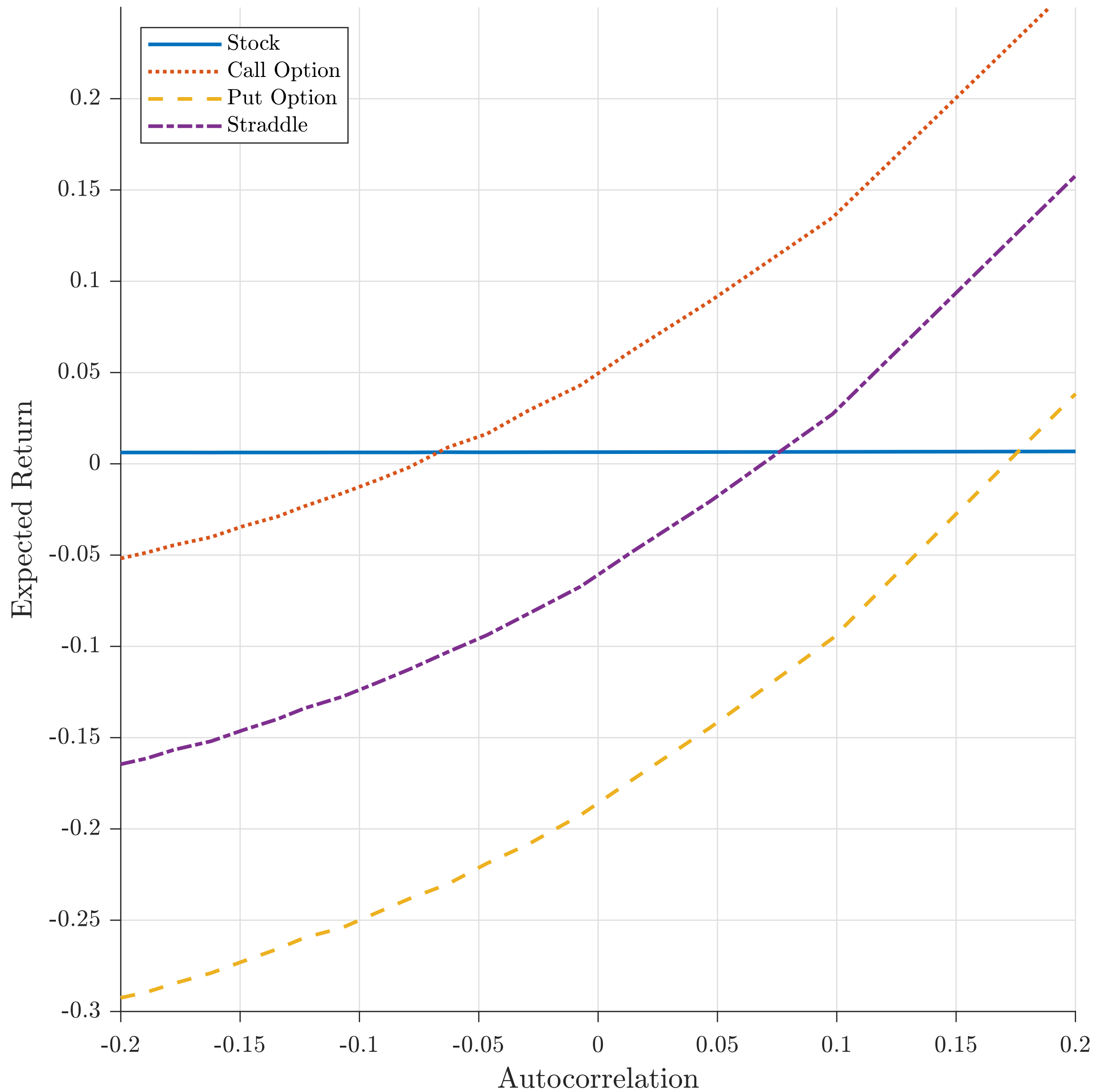

Figure 6
Expected Option Returns under the General Bivariate Trending O-U Process with Stochastic Volatility

This figure plots the expected stock return, expected hold-to-expiration option and straddle returns as functions of first-order autocorrelation of stock returns under the general bivariate trending O-U process with stochastic volatility. The result is based on 6 million simulated random paths. All options are at-the-money options with the following parameters: $\mu = 0.0586$, $r = 0.0225$, $\tau = 1/12$, $\kappa = 5.3178$, $\theta = 0.0408$, $\xi = 0.1882$, $\rho = -0.4694$, $\lambda^{SV} = -1.08$, $\sigma_x = 0.1$, $\lambda = 2.5$ and $\delta = 0.2$.

Online Appendix for
"Stock Return Autocorrelations and Expected Option Returns"

Current Version: March 12, 2023

This document supplements the paper "Stock Return Autocorrelations and Expected Option Returns". It provides additional results and robustness analyses which are not displayed in the published text.

OA.1 Delta-hedged Option Return

As in Goyal and Saretto (2009), we consider static delta-hedged call option gain held-to-expiration given by

$$\Pi^C_{t,T} = C_T - \Delta^C_t S_T - (C_t - \Delta^C_t S_t)e^{r\tau}.$$

Hence, the expected Delta-hedged call option gain held-to-expiration can be computed as

$$\begin{aligned} E_t[\Pi^C_{t,T}] &= E_t[C_T - \Delta^C_t S_T - (C_t - \Delta^C_t S_t)e^{r\tau}] \\ &= E_t[C_T] - \Delta^C_t E_t[S_T] - (C_t - \Delta^C_t S_t)e^{r\tau} \\ &= E_t[C_T] - \Delta^C_t S_t e^{\tau\mu + \frac{\tau\sigma_\tau^2}{2}} - (C_t - \Delta^C_t S_t)e^{r\tau}. \end{aligned}$$

Now, if we take the partial derivative of the above expected gain with respect to σ_τ, which has equivalent sign as taking partial derivative with respect to the first-order autocorrelation, using (A.15) we get

$$\begin{aligned} \frac{\partial E_t[\Pi^C_{t,T}]}{\partial \sigma_\tau} &= \frac{\partial E_t[C_T]}{\partial \sigma_\tau} - \Delta^C_t S_t e^{\tau\mu + \frac{\tau\sigma_\tau^2}{2}} \tau\sigma_\tau \\ &= e^{r\tau} S^*_t \tau\sigma_\tau \left[(\Phi(d^*_1) - \Phi(d_1)) + \frac{\phi(d^*_1)}{\sigma_\tau\sqrt{\tau}} \right]. \end{aligned}$$

For put option, we have

$$E_t[\Pi^P_{t,T}] = E_t[P_T] - \Delta^P_t S_t e^{\tau\mu + \frac{\tau\sigma_\tau^2}{2}} - (P_t - \Delta^P_t S_t)e^{r\tau}.$$

Using (A.16), we get

$$\begin{aligned} \frac{\partial E_t[\Pi^P_{t,T}]}{\partial \sigma_\tau} &= \frac{\partial E_t[P_T]}{\partial \sigma_\tau} - \Delta^P_t S_t e^{\tau\mu + \frac{\tau\sigma_\tau^2}{2}} \tau\sigma_\tau \\ &= e^{r\tau} S^*_t \tau\sigma_\tau \left[-\Phi(-d^*_1) + \frac{\phi(d^*_1)}{\sigma_\tau\sqrt{\tau}} + \Phi(-d_1) \right] \\ &= e^{r\tau} S^*_t \tau\sigma_\tau \left[(\Phi(d^*_1) - \Phi(d_1)) + \frac{\phi(d^*_1)}{\sigma_\tau\sqrt{\tau}} \right] \\ &= \frac{\partial E_t[\Pi^C_{t,T}]}{\partial \sigma_\tau}. \end{aligned}$$

The last equality also follows from the put-call parity. Since $\Phi(-d_1)$ is always positive, if $\partial E_t[P_T]/\partial \sigma_\tau$ was positive, then the delta-hedged put option gain has also positive partial derivative with respect to the first-order autocorrelation. Hence, we conclude that delta-hedged option gain also follow the same pattern as the raw return in our case.

Table OA.1
Description of Control Variables in the Fama-MacBeth Regression

Variable	**Description**
skew	*skew* is the physical skewness calculated using the past 22-day daily returns for each stock.
bm_ratio	*bm_ratio* for June of year $t-1$ to May of year t is computed as the ratio of the book value of common equity in fiscal year $t-1$ to the market value of equity (size) in December of year $t-1$. Book equity is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock.
size	*size* is the natural logarithm of a firm's market cap at the end of each month, and market cap is defined as the product of the closing price and the number of shares outstanding (in millions of dollars).
beta	*beta* is the beta coefficient of each underlying stock based on the CAPM
disp	*disp* is the standard deviation of the analyst forecasts scaled by the mean of analyst forecasts in Diether, Mallowy, and Scherbina (2002) from the IBES.
baspread	*baspread* is the ratio of the difference between the bid and ask quotes of option to the midpoint of the bid and ask quotes at the end of the previous month.
suv	*suv* is defined as the standardized unexpected volume following Garfinkel and Sokobin (2006). It is computed as the standardized prediction error from a regression of trading volume on the absolute value of returns during the week before the end of each month (trading days $[-6,-2]$ relative to the end of each month).
cfv	*cfv* is the cash flow variance, defined as the variance of the monthly ratio of cash flow to the market value of equity over the last 60 months. Cash flow is calculated as net income plus depreciation and amortization, all scaled by the market value of equity.
ch	*ch* is the cash-to-assets ratio, defined as the value of corporate cash holdings over the value of the firm's total assets.
issue_1y	*issue_1y* is the one-year new issues, measured as the log change in shares outstanding from the past 11 months.
pm	*pm* is the profit margin, defined as earnings before interest and tax scaled by revenues.
lnprice	*lnprice* is the natural logarithm of the price at the end of each month.
profit	*profit* is calculated as earnings divided by book equity, in which earnings is defined as income before extraordinary items.
tef	*tef* is the total external financing, defined as net share issuance plus net debt issuance minus cash dividends, scaled by total assets.
z_score	*z_score* is calculated as (1.2×(working capital/assets) + 1.4×(retained earnings/assets) + 3.3×(EBIT/assets) + 0.6×(market value of equity/book value of total liabilities) + (revenues/assets)).

This table lists predictors used as control variables in Table 4 of the Fama-MacBeth regression.

Table OA.2
Portfolio Sorted by Stock Return Autocorrelation

Panel A. Equal-weighted Portfolio

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Low	0.050	−0.143	−0.0055	−0.0068	−0.041	0.0107
2	0.076	−0.129	−0.0036	−0.0048	−0.023	0.0114
3	0.090	−0.124	−0.0034	−0.0047	−0.015	0.0117
4	0.084	−0.097	−0.0021	−0.0042	−0.011	0.0113
High	0.088	−0.079	−0.0017	−0.0040	0.002	0.0105
High-Low	0.037	0.064	0.0038	0.0028	0.043	−0.0002
t-stat	(2.60)	(4.61)	(4.07)	(3.46)	(5.72)	(−0.10)
Two Option-factor alpha	0.043	0.058	0.0050	0.0038	0.043	−0.0011
t-stat	(2.90)	(4.12)	(6.04)	(5.05)	(5.58)	(−0.57)

Panel B: Security Price-weighted Portfolio

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Low	0.040	−0.133	−0.0041	−0.0056	−0.045	0.0098
2	0.070	−0.135	−0.0024	−0.0045	−0.028	0.0116
3	0.090	−0.132	−0.0020	−0.0037	−0.017	0.0123
4	0.082	−0.116	−0.0018	−0.0039	−0.018	0.0125
High	0.076	−0.083	−0.0007	−0.0028	−0.001	0.0118
High-Low	0.036	0.051	0.0034	0.0028	0.043	0.0020
t-stat	(2.35)	(3.31)	(4.11)	(3.54)	(4.96)	(1.16)
Two Option-factor alpha	0.043	0.046	0.0044	0.0036	0.045	0.0013
t-stat	(2.78)	(2.92)	(5.74)	(4.86)	(5.05)	(0.74)

This table summarizes the average returns in monthly frequencies for portfolios sorted by the stock return autocorrelation and hold for one month. Panel A reports the equal-weighted average returns, while Panel B reports the security price-weighted average returns assuming we invest equal shares for all firms in the portfolio. In Panel B, for call option, put option, and stock portfolios, the weights are based on the corresponding security prices. For delta-hedged call, delta-hedged put, and straddle, the weights are based on the initial investment for each firm in the portfolio. We follow Cao, Han, Tong, and Zhan (2021) to construct a two option-factor model: illiquidity and idiosyncratic volatility. The factor realizations in each month are obtained as the high-minus-low spread returns of stock value-weighted portfolios of writing delta-neutral calls sorted on the idiosyncratic volatility or the Amihud illiquidity measure of the underlying stock. The alpha is calculated based on the two option-factor model. The sample period is from January 1996 to December 2020.

Table OA.3
Option Portfolios Double Sorted by Stock Return Autocorrelation and Other Stock Characteristics

Panel A: Double Sorting Call Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.061	0.086	0.060	0.035	0.031
t-stat of α	(2.60)	(3.66)	(2.75)	(1.50)	(1.18)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.071	0.071	0.070	0.041	0.002
t-stat of α	(2.88)	(3.13)	(3.14)	(1.75)	(0.06)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.038	0.032	0.062	0.037	0.064
t-stat of α	(1.63)	(1.40)	(2.65)	(1.55)	(2.85)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.051	0.034	0.033	0.023	0.053
t-stat of α	(2.23)	(1.45)	(1.39)	(1.02)	(1.95)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.012	0.053	0.040	0.074	0.025
t-stat of α	(0.54)	(2.31)	(1.70)	(3.37)	(1.05)
Panel B: Double Sorting Put Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.012	0.054	0.064	0.094	0.022
t-stat of α	(0.45)	(2.53)	(3.27)	(4.12)	(0.93)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.028	0.040	0.086	0.029	0.062
t-stat of α	(1.01)	(1.92)	(4.12)	(1.24)	(2.76)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.089	0.048	0.065	0.051	0.059
t-stat of α	(4.19)	(1.96)	(3.00)	(2.26)	(2.73)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.055	0.075	0.058	0.039	0.073
t-stat of α	(2.46)	(3.24)	(2.51)	(1.98)	(3.01)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.087	0.058	0.049	0.049	0.061
t-stat of α	(4.52)	(2.62)	(2.11)	(2.40)	(2.71)

In this table, we conduct an unconditional sorting based on a certain stock characteristic and stock return autocorrelation, in total twenty-five bins in two dimensions. We classify a certain security into each bin based on the cutoffs of the sorted characteristic and stock return autocorrelation. ILIQ stands for the stock illiquidity computed following Amihud (2002) and IVTS denotes the implied volatility term structure defined in Section 3. Within each bin we compute the difference of average returns between the high and low stock return autocorrelation quintile. We follow Cao et al. (2021) to construct a two option-factor model: illiquidity and idiosyncratic volatility. The factor realizations in each month are obtained as the high-minus-low spread returns of stock-value-weighted portfolios of writing delta-neutral calls sorted on the idiosyncratic volatility or the Amihud illiquidity measure of the underlying stock. We report the alpha and the corresponding t-stat based on the two option-factor model for equal-weighted call and put option portfolios.

Table OA.4
Option Portfolios Double Sorted by Stock Return Autocorrelation and Other Stock Characteristics

Panel A: Double Sorting Delta-hedged Call Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.002	0.005	0.005	0.007	0.008
t-stat	(2.89)	(5.06)	(4.54)	(3.91)	(3.36)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.004	0.005	0.006	0.006	0.006
t-stat	(3.93)	(4.90)	(4.83)	(3.82)	(2.67)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.006	0.003	0.004	0.005	0.004
t-stat	(3.94)	(2.56)	(3.71)	(3.76)	(2.49)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.003	0.004	0.003	0.004	0.006
t-stat	(2.85)	(2.96)	(2.22)	(2.93)	(2.97)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.004	0.005	0.003	0.005	0.005
t-stat	(2.22)	(3.58)	(2.72)	(4.43)	(3.36)
Panel B: Double Sorting Delta-hedged Put Option Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.002	0.004	0.005	0.007	0.003
t-stat	(2.16)	(3.99)	(4.20)	(4.43)	(1.56)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.003	0.004	0.005	0.005	0.002
t-stat	(2.83)	(4.59)	(4.62)	(3.19)	(1.22)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.004	0.002	0.004	0.004	0.004
t-stat	(2.98)	(1.46)	(3.09)	(3.23)	(2.52)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.003	0.003	0.003	0.002	0.004
t-stat	(2.94)	(2.46)	(2.33)	(1.59)	(2.03)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.003	0.004	0.003	0.004	0.003
t-stat	(2.12)	(2.87)	(2.18)	(3.90)	(2.08)

In this table, we conduct an unconditional sorting based on a certain stock characteristic and stock return autocorrelation, in total twenty-five bins in two dimensions. We classify a certain security into each bin based on the cutoffs of the sorted characteristic and stock return autocorrelation. ILIQ stands for the stock illiquidity computed following Amihud (2002) and IVTS denotes the implied volatility term structure defined in Section 3. Within each bin we compute the difference of average returns between the high and low stock return autocorrelation quintile. We show the results for equal-weighted delta-hedged call and delta-hedged put portfolios.

Table OA.5
Option Portfolios Double Sorted by Stock Return Autocorrelation and Other Stock Characteristics

Panel A: Double Sorting Straddle Return					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.049	0.058	0.042	0.055	0.026
t-stat	(3.51)	(4.40)	(3.31)	(4.16)	(1.66)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.056	0.048	0.057	0.038	0.025
t-stat	(3.81)	(3.85)	(4.79)	(2.83)	(1.66)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.049	0.033	0.055	0.052	0.050
t-stat	(3.88)	(2.66)	(4.49)	(3.74)	(3.78)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.049	0.049	0.042	0.037	0.022
t-stat	(4.40)	(3.78)	(3.37)	(2.71)	(1.15)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
High ρ − Low ρ	0.041	0.053	0.040	0.052	0.040
t-stat	(3.00)	(4.28)	(2.93)	(4.21)	(3.09)
Panel B: Double Sorting Straddle Return (Alpha)					
Sorted by Realized Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.045	0.056	0.041	0.053	0.022
t-stat of α	(3.15)	(4.21)	(3.15)	(3.91)	(1.37)
Sorted by Idiosyncratic Volatility	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.058	0.042	0.057	0.035	0.024
t-stat of α	(3.81)	(3.30)	(4.65)	(2.53)	(1.53)
Sorted by Variance Risk Premium	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.049	0.032	0.061	0.048	0.046
t-stat of α	(3.84)	(2.48)	(4.87)	(3.38)	(3.41)
Sorted by ILIQ	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.049	0.050	0.038	0.032	0.010
t-stat of α	(4.40)	(3.83)	(2.99)	(2.30)	(0.50)
Sorted by IVTS	**Low**	**2**	**3**	**4**	**High**
α of High ρ − Low ρ	0.040	0.049	0.039	0.054	0.042
t-stat of α	(2.83)	(3.88)	(2.77)	(4.22)	(3.20)

In this table, we conduct an unconditional sorting based on a certain stock characteristic and stock return autocorrelation, in total twenty-five bins in two dimensions. We classify a certain security into each bin based on the cutoffs of the sorted characteristic and stock return autocorrelation. ILIQ stands for the stock illiquidity computed following Amihud (2002) and IVTS denotes the implied volatility term structure defined in Section 3. Within each bin we compute the difference of average returns between the high and low stock return autocorrelation quintile. In Panel A, we show the results for equal-weighted straddle portfolios. In Panel B, we follow Cao et al (2021) to construct a two option-factor model: illiquidity and idiosyncratic volatility. The factor realizations in each month are obtained as the high-minus-low spread returns of stock-value-weighted portfolios of writing delta-neutral calls sorted on the idiosyncratic volatility or the Amihud illiquidity measure of the underlying stock. We report the alpha and the corresponding t-stat based on the two option-factor model for straddle portfolios.

Table OA.6
Fama-Macbeth Regressions with Stock Return Autocorrelation

	Call Option	Put Option	Delta-hedged Call	Delta-hedged Put	Straddle	Underlying Stock
Intercept	7.761	−11.415	−0.326	−0.490	−1.766	1.113
t-stat	(2.42)	(−2.28)	(−1.70)	(−2.74)	(−0.98)	(2.74)
Autocorrelation	1.200	2.284	0.125	0.083	1.363	−0.009
t-stat	(2.48)	(4.87)	(3.86)	(2.97)	(5.67)	(−0.12)
Average adj. R^2 (%)	0.29	0.32	0.25	0.26	0.28	0.54

This table reports the Fama-MacBeth regressions for each dependent variable that is the return of different securities specified at the top of each column. The independent variable is stock return autocorrelation. All predictors are normalized to have mean zero and standard deviation of one at each month. The detailed cross-sectional regression and time-series test are specified in Section 3.3. All dependent and independent variables are expressed as monthly values and the coefficients are multiplied by 100. The coefficients in the table are calculated by taking the time-series average of the cross-sectional regressions over time. The t-stat reported is the t-test with Newey-West one-lag correction. The sample period is from January 1996 to December 2020.

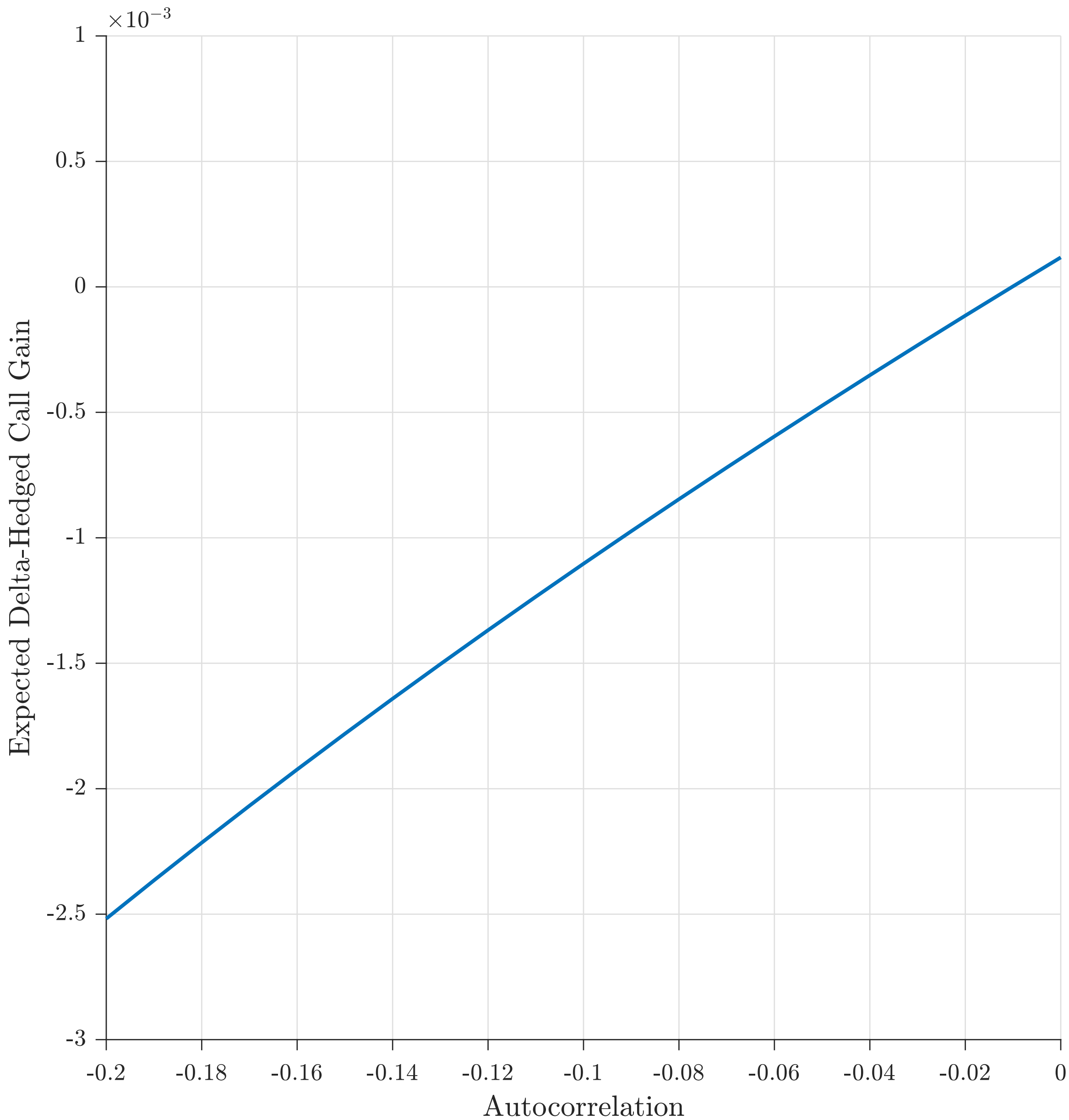

Figure OA.1
Expected Delta-hedged Call Option Gain under the Trending O-U Process
This figure plots the expected hold-to-expiration call option gain as a function of first-order autocorrelation of stock returns under the trending O-U process. All options are at-the-money options with the following parameters: $\mu = 0.10$, $r = 0.05$, $\tau = 1/12$, and $\sigma = 0.2$.