The Early Exercise Risk Premium*

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This Draft: August 8, 2023

Abstract

We study the asset pricing implications of being able to optimally early exercise plain-vanilla puts, contrasting expected raw and delta-hedged returns across equivalent American and European puts. Our theory suggests that American puts yield less negative raw but more negative delta-hedged expected returns than equivalent European puts. The raw (delta-hedged) spread widens with a higher early exercise probability, as induced through, for example, moneyness, time-to-maturity, and underlying-asset volatility (variance and jump risk premiums). An empirical comparison of single-stock American puts with equivalent synthetic European puts formed from put-call parity supports our theory if and only if we allow for optimal early exercises in our return calculations. More strikingly, allowing for optimal early exercises significantly alters the profitability of 14 out of 15 well-known option anomalies, with the average absolute change equal to 32% and five anomalies becoming insignificant.

Keywords: Empirical asset pricing; cross-sectional option pricing; put options; early exercise.

JEL classification: G11, G12, G13.

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*We are greatly indebted to Lukas Schmid (our department editor), an anonymous associate editor, and two referees for insightful and constructive advice helping us to broaden our contribution. We are also indebted to Carol Alexander, Michael Brennan, Steve Figlewski, Massimo Guidolin, Kris Jacobs, Julia Kapraun, Olga Kolokolova, Alex Kostakis, Hugues Langlois, Hening Liu, Kevin Schneider, Tyler Shumway, Roméo Tédongap, Christian Wagner, Bob Whaley, and seminar or conference participants at Alliance Manchester Business School, Aston Business School, Lancaster University Management School, Paris-Dauphine University, the 35th Annual Conference of the French Finance Association (Paris), the 5th Young Finance Scholars Conference (Brighton), the 2018 European Financial Management Association Meeting (Milan), the 2018 Frontiers of Factor Investing Conference (Lancaster), the 4th Konstanz-Lancaster Workshop on Finance and Econometrics (Konstanz), and the 2020 Financial Management Association Annual Meeting (virtual) for further suggestions.

1 Introduction

Although a large empirical literature looks into American option returns, most studies in that literature do not consider that it can sometimes be optimal to exercise those options before their maturity date. While cross-sectional option pricing studies, for example, aim to identify factors explaining the cross-section of American option returns, they generally disregard the possibility of an optimal early exercise in their return calculations, implicitly assuming that American options are sufficiently similar to European options to treat them as if they were European options. Yet, despite this common tendency in the literature, there are no studies formally evaluating the differences in returns across these two types of options.[1]

In our work, we make a first step toward closing this gap in the literature, studying how the ability to optimally early exercise a plain-vanilla put affects its expected return. On the theoretical front, we simulate asset-value paths under the physical and risk-neutral measure to calculate the expected returns of equivalent (i.e., same underlying asset, strike price, and maturity date) American and European puts. The simulations suggest that the spread in the expected *raw* returns between those puts ("the early exercise risk premium in puts") is positive and economically large, while the spread in their expected *delta-hedged* returns ("the delta-hedged premium") is negative, economically meaningful, but an order of magnitude smaller than the spread in expected raw returns. The simulations further indicate that both premiums positively vary with determinants of the optimal early exercise probability. On the empirical front, a comparison of single-stock American puts and equivalent *synthetic* European puts derived from put-call parity supports our theoretical predictions *if and only if* we allow for optimal early exercises in our return calculations. More strikingly, allowing for such exercises significantly changes the profitability of 14 out of 15 well-known option return anomalies, with

[1]The sentiment that American and European options are similar is often accredited to Brennan and Schwartz (1977) and Broadie et al. (2007). Using various stochastic processes, they show that the two types of options have similar values. Notice, however, that they only look into values, and not returns.

the average absolute change in the mean spread returns of the anomalies equal to 32% and five anomalies becoming statistically insignificant at the 95% confidence level.

In our theoretical work, we rely on Longstaff and Schwartz's (2001) method to contrast the expected returns of equivalent American and European puts. Specifically, we simulate daily underlying-asset-value paths under the physical and risk-neutral measure from a geometric Brownian motion (GBM), a stochastic volatility (SV), and a stochastic volatility-jump (SVJ) model calibrated to single stocks (see, e.g., Bates (1996), Broadie et al. (2009), and Pollastri et al. (2023)). We then compute the expected European put return as the ratio of the mean put payoff under the physical measure to the mean discounted maturity payoff under the risk-neutral measure. Conversely, we compute the American put return by first backing out the optimal early exercise boundary (i.e., the set of highest underlying asset values for which an early exercise is optimal) over the time-to-maturity. In complete agreement with before, we next compute the ratio of the mean compounded earliest put payoff under the physical measure to the mean discounted earliest put payoff under the risk-neutral measure.

Our simulation exercise reveals that American puts generally have higher (i.e., less negative) expected returns than their equivalent European puts. The reason is that although, in line with Merton (1973), the American puts always have higher values than their counterparts, they have, in proportional terms, even higher expected payoffs. Remarkably, even the simple GBM process yields an expected return spread of 2.45% *per month* under standard parameter values.[2] In comparison, the more sophisticated SV and SVJ processes yield spreads within the same ballpark. Independent of the stochastic process, the spread strongly rises with moneyness but falls with time-to-maturity and underlying asset volatility, consistent with it being positively associated with the optimal early exercise probability. Fixing the former Black-Scholes (1973) effects, the spread is also more weakly related to stochastic volatility and jump effects. A more

[2]In the example, we use a strike-to-stock price ratio of 1.05, a time-to-maturity of one month, an annualized underlying-asset volatility of 30%, and an annualized riskfree rate of return of 2.5%.

negative variance or jump risk premium, for example, consistently decreases the spread, implying a negative (and not positive) delta-hedged early exercise risk premium.

In our empirical work, we use the ex-post raw and delta-hedged returns of exchange-traded single-stock American puts and equivalent synthetic European puts to test our theoretical predictions. We calculate the monthly American put return as the compounded early exercise payoff (optimal early exercise case) or the end-of-month put price (no such exercise case) to the start-of-month price, comparing the early exercise payoff with the price at the end of each trading day to identify optimal early exercises (Barraclough and Whaley's (2012) "market rule"). In addition, we however also calculate never-early-exercised American put returns to benchmark against other studies. To calculate the monthly European put return, we start from Merton's (1973) insight that it is never optimal to early exercise American calls written on zero-dividend assets, allowing us to treat these as *quasi-European* calls. We then recall that a European put can be replicated using a portfolio long the equivalent European call, long a money-market investment, and short the underlying asset ("put-call parity;" see Zivney (1991)). We finally calculate the monthly synthetic European put return as the end-of-month synthetic portfolio value to its start-of-month value. We also calculate delta-hedged returns by subtracting the compounded value of the put replication portfolio plus the financing cost at the end of the month from the numerator of each put's return and replacing the denominator with the absolute start-of-month value of the delta-hedged position (Cao and Han (2013)).

Our empirical evidence derived from both portfolio sorts and Fama-MacBeth (FM; 1973) regressions supports our theoretical predictions. In the pooled data, the spread portfolio long single-stock American puts and short their equivalent synthetic European puts, for example, yields a mean monthly raw return of 2.38% (t-statistic: 5.58) and a mean monthly delta-hedged return of –0.50% (t-statistic: –12.20). Unsurprisingly, both t-statistics are far outside their bootstrapped 99% confidence intervals. More remarkably, the mean returns are largely attributable to optimal early exercises of the American puts, with the mean raw and delta-hedged returns changing to –0.89% (t-statistic: –3.75) and –0.22% (t-statistic: –9.36) upon not allowing for such exercises, respectively. Further supporting our theory, the mean raw return significantly rises (falls) with moneyness (days-to-maturity and stock volatility) when we allow for optimal early exercises, but either fails to do so or does so far more weakly when we do not allow for such exercises. Conversely, the mean delta-hedged return falls with stock volatility (a variance risk premium proxy in these tests) when we allow for optimal early exercises, but does so far more weakly when we do not allow for such exercises.

We finally evaluate the implications of our findings for the cross-sectional option return literature. To do so, we select 15 well-known option return anomalies, contrasting their mean spread portfolio returns across the case in which we do and the case in which we do not allow for optimal early exercises in our return calculations. Noteworthily, our evidence suggests that all anomalies still exist over our updated sample period when we exactly replicate prior studies and do not allow for optimal early exercises. More importantly, allowing for optimal early exercises significantly alters the mean spread portfolio returns of 14 anomalies, with the mean absolute percentage change around 32%. Consistent with either the long or short portfolio containing more high-early-exercise-probability puts, the mean spread portfolio returns of nine (five) anomalies significantly move away from (toward) zero, with all mean returns moving toward zero becoming statistically insignificant at the 95% confidence level.

Our work adds to empirical studies comparing the spreads in prices across American and equivalent European options ("the early exercise premium"). While Zivney (1991), de Roon and Veld (1996), and Engström and Nordén (2000) conduct that exercise on traded American and equivalent synthetic European options, McMurray and Yadav (2000) conduct it on traded American and European options with, however, slightly different strike prices. Supporting Merton (1973), they all find a positive early exercise premium. In contrast to them, we study the spread in expected returns (and not prices) between those two types of options. Given that the ability to early exercise affects both an option's expected payoff *and* price, our conclusions do not follow mechanically from theirs. In fact, if we exclusively focused on the price effect, we would reach exactly the opposite conclusions from those outlined in our work.

We further add to studies looking into the pricing of stock and option characteristics in the cross-section of option returns. Studying raw option returns, Coval and Shumway (2001) and Ni (2009) consider moneyness; Hu and Jacobs (2020) and Aretz et al. (2023) total, systematic, and idiosyncratic underlying-asset volatility; and Boyer and Vorkink (2014) option return skewness. Turning to delta-hedged options or straddles, Goyal and Saretto (2009) investigate the realized-to-implied volatility ratio of the underlying asset; Cao and Han (2013) idiosyncratic underlying-asset volatility; Vasquez (2017) the slope of the implied volatility term structure; Ruan (2020) and Cao et al. (2023) the volatility of variance; and Zhan et al. (2022) stock anomaly variables. Karakaya (2013) and Büchner and Kelly (2021) develop the first factor models to price delta-hedged options. We contribute to these studies by demonstrating that their pricing results significantly change upon allowing for optimal early exercises.

We finally relate to studies looking into the early exercise policies of real investors (see Overdahl and Martin (1994), Finucane (1997), and Poteshman and Serbin (2003)). In line with the general consensus in that literature, Pool et al. (2008) estimate that the total profits lost from investors suboptimally early exercising single-stock calls on ex-dividend dates amounts to $491 million over a ten-year period. Barraclough and Whaley (2012) estimate that the corresponding number for single-stock puts is $1.9 billion over a 13-year period. Given these estimates, it is noteworthy that we find that optimal early exercises are priced in the data in accordance with neoclassical models assuming optimal policies, possibly suggesting that real-world deviations from these policies are not as stark as often believed.

We proceed as follows. Section 2 studies the raw and delta-hedged early exercise risk premium in neoclassical models. While Section 3 offers our main cross-sectional evidence, Section 4 presents our replication exercise. Section 5 concludes. We offer the results from additional simulation exercises and robustness tests in the Internet Appendix.

2 Theory

In this section, we evaluate the raw and delta-hedged early exercise risk premium in puts in standard neoclassical models. To do so, we first explain why we would expect the raw premium to be positive. We next back up our expectation through a Monte Carlo simulation exercise in which we rely on Longstaff and Schwartz's (2001) method in conjunction with well-known stochastic processes to calculate expected American and European put returns.

2.1 The Intuition Behind the Early Exercise Risk Premium

We generate some intuition about the early exercise risk premium by recalling that we can replicate an American put by longing the equivalent European put plus an exotic derivative paying out the interest rate times the strike price in optimal-early-exercise states (Carr et al. (1992)). To better understand that, assume we hold an American put which should optimally not be early exercised on the current date ($t = 0$). Whenever the underlying asset's value $S(t)$ drops to or below the optimal early exercise threshold $B(t)$ over the put's lifetime, we early exercise the put, using the proceeds to acquire a portfolio long an investment of the strike price K into a money market account and short the underlying asset. Conversely, in the opposite case, we sell the portfolio and use the proceeds to buy back the put. On the maturity date T, the strategy's payoff is then zero if we own the put but $K - S(T)$ if we own the portfolio — and thus exactly identical to the maturity payoff of the equivalent European put.

Despite the exactly identical maturity payoffs, the replication strategy however also earns interest on the money market investment equal to $r_f K dt$ whenever $S(t)$ is equal to or below $B(t)$, where r_f is the interest rate. Since we do not require the interest to buy back the put, it can be immediately consumed. Given that, an American put is equivalent to its equivalent European put plus an infinite number of binary cash-or-nothing puts (the exotic derivative), with the binary put maturing at time t^b yielding a payoff of $r_f K dt$ if $S(t^b) \leq B(t^b)$ and else zero. Since, conditional on a non-zero payoff, only the payoff of the European put but not those of the binary puts negatively covary with the underlying asset's value, the European put typically has a lower (i.e., more negative) systematic risk and thus expected return than the binary puts.[3] In turn, the American put then typically has a higher expected return than the equivalent European put.

Also noteworthy, since the value of the exotic derivative is a function of the risk-neutral optimal early exercise probability (see Carr et al. (1992, p.91)), a higher probability raises the value of that derivative. In turn, the expected American put return is skewed more toward the expected exotic derivative return, inflating the early exercise risk premium.

2.2 Monte Carlo Simulation Exercise

2.2.1 Calculating Simulated Expected Put Returns

We next run a Monte Carlo simulation exercise to verify our intuition that the early exercise risk premium should be positive in the vast majority of cases. To that end, we use Longstaff and Schwartz's (2001) method in conjunction with alternative stochastic processes to compute the expected returns of American and European puts on zero-dividend assets. As alternative processes, we choose geometric Brownian motion (GBM), a stochastic volatility (SV) process, and a stochastic volatility plus asset-value jumps (SVJ) process (see Bates (1996), Andersen

[3] In a Black-Scholes (1973) world, it is easy to demonstrate that the expected return of a binary cash-or-nothing put is bounded from below by the expected return of the equivalent European put. Notwithstanding, since the cash-or-nothing puts making up the exotic derivative have lower strike prices (raising their expected returns) and shorter times-to-maturity (lowering their expected returns) than the European put, we cannot categorically rule out that they could have lower expected returns than the European put.

et al. (2002), and Pollastri et al. (2023)).[4] We can compactly write the processes as:

$$dS(t) = \alpha S(t)dt + S(t)\sqrt{V(t)}dW^S(t) + d\left(\sum_{j=1}^{N(t)} S(\tau_{j-})\left[e^{Z_j^s} - 1\right]\right) - \lambda\bar{\mu}S(t)dt, \quad (1)$$

$$dV(t) = \kappa(\theta - V(t))dt + \sigma_v\sqrt{V(t)}dW^v(t), \quad (2)$$

where $S(t)$ and $V(t)$ are, respectively, the asset value and asset variance at time t, α the asset value drift rate, κ the mean reversion in variance speed, θ the long-run variance, and σ_v the volatility of variance. Next, $W^S(t)$ and $W^v(t)$ are correlated Brownian motions with correlation coefficient ρ. Finally, $N(t)$ is a Poisson process with intensity λ, $S(\tau_{j-})$ is the asset value directly before a jump, $Z_j^s \sim N(\mu_z, \sigma_z^2)$, and $\bar{\mu} = e^{\mu_z + \sigma_z^2/2} - 1$.

To rule out jumps, the SV model sets the jump intensity λ to zero. Conversely, to ensure that the asset-value variance is constant, the GBM model further sets the mean reversion speed κ and the volatility of variance σ_v to zero. Since jumps, however, add to variance, we follow Broadie et al. (2009) in subtracting $\lambda((\mu_z)^2 + (\sigma_z)^2)$ from θ to prevent jumps from changing long-run variance (which is $\theta + \lambda((\mu_z)^2 + (\sigma_z)^2)$). Given that, our simulations ensure that the first two moments do not vary across the stochastic processes.

We simulate asset values from Equations (1) and (2) under both the physical ($\mathbb{P}$) and the risk-neutral ($\mathbb{Q}$) probability measure, indicating the parameter values under the physical measure with a $\mathbb{P}$ (e.g., $\kappa^{\mathbb{P}}$) and those under the risk-neutral measure with a $\mathbb{Q}$ (e.g., $\kappa^{\mathbb{Q}}$) superscript. By construction, the asset value drift α is equal to the risk-free rate of return r_f under the risk-neutral measure, implying $\alpha^{\mathbb{Q}} = r_f$. To determine the relations between the other physical and risk-neutral parameter values, we follow Cox et al. (1985) and Pan (2002) in assuming

[4] We also looked into an extended version of the SVJ model featuring correlated asset-value as well as volatility jumps (see Eraker's (2004) SVCJ model). Since the conclusions obtained from that model are, however, close-to-identical compared to those obtained from the SVJ model, we do not report them.

that the market price of variance risk $\Phi(t)$ is linear in the asset's volatility $\sqrt{V(t)}$:

$$\Phi(t) = \gamma\sigma_v^{\mathbb{P}}\sqrt{V(t)}, \tag{3}$$

where γ is a parameter. The volatility of variance σ_v and the correlation coefficient ρ are then equal under the two measures, implying $\sigma_v^{\mathbb{P}} = \sigma_v^{\mathbb{Q}}$ and $\rho^{\mathbb{P}} = \rho^{\mathbb{Q}}$. Conversely, the mean reversion speed κ and the long-run variance θ under the measures are linked through $\kappa^{\mathbb{Q}} = \kappa^{\mathbb{P}} + \gamma(\sigma_v^{\mathbb{P}})^2$ and $\theta^{\mathbb{Q}} = \kappa^{\mathbb{P}}\theta^{\mathbb{P}}/(\kappa^{\mathbb{P}} + \gamma(\sigma_v^{\mathbb{P}})^2)$. We finally follow Bates (1996) in assuming the existence of a representative agent. The jump volatility σ_z is then equal under the two measures, implying $\sigma_z^{\mathbb{P}} = \sigma_z^{\mathbb{Q}}$, while the jump intensity λ and the mean jump size μ_z are related through $\lambda^{\mathbb{Q}} = \lambda^{\mathbb{P}}E(1 + \Delta J_w/J_w)$ and $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}} + cov(Z_j^s, \Delta J_w/J_w)/E(1 + \Delta J_w/J_w)$, where $\Delta J_w/J_w$ is the percentage change in the marginal utility of the agent upon a jump.

After simulating a large number of sample paths for the underlying asset's value over the time-to-maturity under the $\mathbb{P}$ and the $\mathbb{Q}$ measure using one of the stochastic processes, we compute the expected European put return as the simple mean of the put's value at the end of the investment horizon (which may be earlier than the maturity date) taken over the paths scaled by its initial value. We use the well-known European option valuation closed-form solutions of Black and Scholes (1973), Heston (1993), and Bates (1996) to compute the put's value both on the initial date and at the end of the investment horizon (so that we only require the simulations under the $\mathbb{P}$ measure to compute the expected European put return).

Relying on the same sample paths, we compute the expected American put return by first delineating the optimal early exercise threshold (i.e., the set of highest underlying asset values for which an early exercise is optimal) over the time-to-maturity. To do so, we rely on the simulations under the $\mathbb{Q}$ measure and calculate the put's path-specific maturity payoff, $\max(K - S(T), 0)$, where K is the strike price. Moving back one time step to date $T-1$, we regress the path-specific maturity put payoff discounted to date $T-1$ on a higher-order polynomial of the path-specific asset value on the same date, using, however, only observations for which the put is in-the-money (ITM) on date $T-1$. We then assume an optimal early exercise under a path and on that date if the early exercise payoff, $\max(K - S(T-1), 0)$, exceeds the fitted regression value. We proceed in that manner, always moving back one time step, regressing the path-specific earliest early exercise or maturity payoff discounted to that date on the higher-order polynomial of the path-specific asset value on the same date using only ITM observations, and determining optimal early exercises on that date.

We next calculate the expected American put return as the simple mean of the put's payoff at the end of the investment horizon taken over the sample paths under the $\mathbb{P}$ measure scaled by its initial value. In this case, the put's payoff at the end of the investment horizon is however either the earliest early exercise payoff compounded to that date (if the asset value drops below the early exercise threshold over the investment horizon) or the put's value on that date (if it does not). We obtain the put's value at the end of the investment horizon from a regression modelling the discounted earliest early exercise or maturity payoff under the $\mathbb{Q}$ measure as a function of the asset's value similar to the one in the prior paragraph.[5] Conversely, we calculate the put's initial value as the simple mean of the discounted earliest exercise or maturity payoff on the contract initiation date taken over the sample paths under the $\mathbb{Q}$ measure.

As basecase parameter values, we choose an initial asset value, $S(0)$, of 50, a physical annual drift rate, $\alpha^{\mathbb{P}}$, of 12%,[6] an initial annual volatility, $\sqrt{V(0)}$, of 30%, and an annual risk-free rate, r_f, of 2.5%. We always set the physical long-run variance, $\theta^{\mathbb{P}}$, to the current variance. We select a strike price, K, of 50 and a time-to-maturity, T, of 30 days. Since we use single-stock

[5]While we could have relied on a polynomial regression to model the put's value at the end of the investment horizon as a function of the underlying asset's value, a downside to that strategy is that such a regression can yield negative values, especially for out-of-the-money (OTM) puts. To avoid negative values, we have, in this one case, resorted to a regression on dummy variables indicating in which dollar cent interval the value of the underlying asset lies, letting the intervals range from five standard deviations below the expected underlying asset value to five standard deviations above that value in increments of one dollar cent.

[6]We also looked into lower physical annual drift rates, verifying that the early exercise risk premium remains economically meaningful even for annual drift rates equal to 8.50% or 10.50%.

puts in our empirical work, we set the basecase values for the other parameters close to the mean estimates obtained in Pollastri et al. (2023) from calibrating the SV and SVJ stochastic processes to the single stocks in the S&P 500. Specifically, we choose a mean reversion speed, $\kappa^{\mathbb{P}}$, of 6.00, an annual volatility of variance, $\sigma_v^{\mathbb{P}}$, of 40%, and a correlation coefficient, $\rho^{\mathbb{P}}$, of –0.25 under the physical measure. We select an annual jump intensity, $\lambda^{\mathbb{P}}$, of 3.50, a mean jump size, $\mu_z^{\mathbb{P}}$, of 1%, and a jump volatility, $\sigma_z^{\mathbb{P}}$, of 6% under the same measure. In line with Ang et al.'s (2006) evidence, we set the variance risk premium parameter, γ, to –4.00.[7]

We next assume that the expected marginal utility change upon a jump, $E(1+\Delta J_w/J_w)$, is 1.25, and that the scaled covariance between that change and the jump, $cov(Z_j^s, \Delta J_w/J_w)/E(1+\Delta J_w/J_w)$, is –0.04, so that jumps occur more frequently and are more likely to be downward in recession states. We then finally calculate the risk-neutral values of the additional SV model parameters, $\kappa^{\mathbb{Q}}$, $\theta^{\mathbb{Q}}$, $\sigma_v^{\mathbb{Q}}$, and $\rho^{\mathbb{Q}}$, and the SVJ model parameters, $\lambda^{\mathbb{Q}}$, $\mu_z^{\mathbb{Q}}$, and $\sigma_z^{\mathbb{Q}}$, from the aforementioned relations between the physical and risk-neutral parameters.

In each simulation, we rely on five million asset-value paths sampled at a daily frequency to calculate the expected American and European put returns. We use a third-order polynomial as regression function to estimate a put's value. In line with our empirical work, we always choose a 30-day (i.e., one month) investment horizon, so that our basecase 30-day puts are held-to-maturity, while our longer days-to-maturity puts are sold-before-maturity.[8]

2.2.2 The Theoretical Early Exercise Risk Premium

In Table 1, we study the early exercise risk premium in puts in a GBM world. To that end, we report the expected payoffs, values, and expected returns of the American (columns (1) to (3))

[7] Ang et al. (2006) report that their average single stock yields an annual variance risk premium close to –6%. Under our basecase parameters, the market price of variance risk, $\Phi(t)$ (i.e., the variance risk premium scaled by the volatility of variance), is –0.50 and the variance risk premium parameter, γ, –4.00, close to the estimates in Bates (2000), Eraker (2004), and Jacobs and Liu (2019) obtained from stock indexes.

[8] In the Internet Appendix, we briefly review papers mathematically proving that the Longstaff-Schwartz (2001) option value estimate converges to the true value with the number of sample paths in the GBM, SV, and SVJ worlds. We also demonstrate that our estimates are reasonably close to convergence.

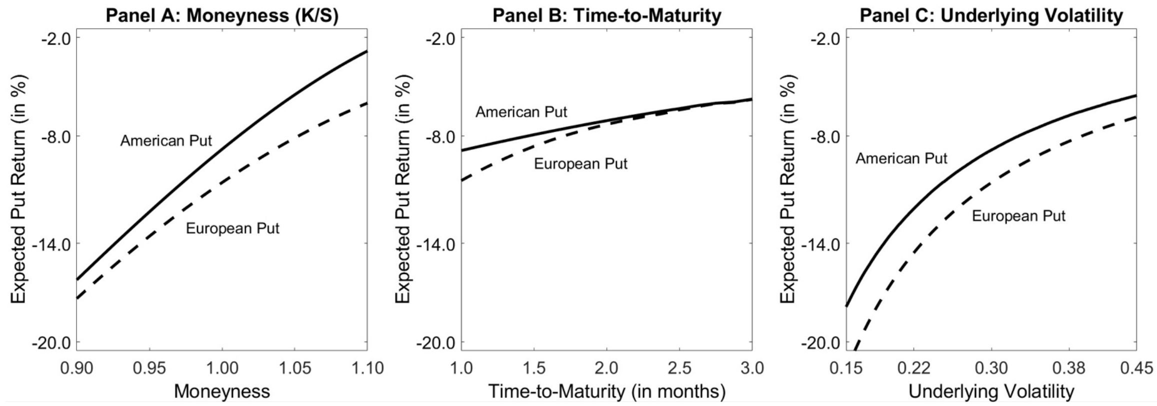

Figure 1: Put and Stock Characteristics and the Early Exercise Risk Premium The figure plots the effects of moneyness (Panel A), days-to-maturity (Panel B), and underlying asset volatility (Panel C) on the theoretical GBM-world early exercise risk premium in puts. We let moneyness range from 0.90 to 1.10, days-to-maturity from 30 (one month) to 90 (three months) days, and underlying-asset volatility from 15% to 45% per annum. We describe the basecase parameter values in Section 2.2.1.

and European ((4) to (6)) puts plus the differences in these statistics across the two option types (remaining columns), all respectively. While Panels A, B, and C focus on ITM (strike-to-stock price ratio = 1.05), at-the-money (ATM; 1.00), and OTM (0.95) puts, the rows within each panel further distinguish between puts with a short (30 days), intermediate (60), and long (90) time-to-maturity and those written on assets with a low (15%), intermediate (30%), and high (45%) annualized volatility. As said before, since the investment horizon is always 30 days long, the 30 (more) days-to-maturity puts are held-to-maturity (sold-before-maturity). While we consistently used the delta-method to calculate standard errors for all raw and delta-hedged early exercise risk premiums obtained from our simulations (see Cochrane (2005, pp. 195-196)), we found those to be so negligible that we refrain from explicitly reporting them.[9]

TABLE 1 ABOUT HERE

The table shows that the early exercise risk premium in puts in column (3)–(6) is positive

[9]For example, while we find that the raw early exercise risk premium of 30-day ATM puts on 30% volatility assets is 1.827% in the GBM world, its standard error is 0.010%. The upshot is that the one-standard-error bounds are 1.817% and 1.837%, hardly affecting our conclusions.

but varies markedly with put as well as asset characteristics. Specifically, the premium ranges from a minimum of essentially zero (see the longer-ahead OTM puts in Panel C) to a maximum of 6.82% (see row 1 in Panel A). Interestingly, variations in the premium can be traced to variations in moneyness, time-to-maturity, and asset volatility, with the premium rising with moneyness but falling with time-to-maturity and asset volatility. An important exception occurs for deeper OTM puts with a longer time-to-maturity which can yield a mildly positive (and not negative) early exercise risk premium-asset volatility relation. The conditioning ability of the characteristics arises directly from them being determinants of the optimal early exercise probability, with a higher moneyness (lower time-to-maturity or asset volatility) typically raising that probability.[10] Figure 1 graphically shows the effects of moneyness (Panel A), days-to-maturity (Panel B), and asset volatility (Panel C) on the early exercise risk premium.

Looking into the components of the early exercise risk premium in columns (3) and (6), the table further reveals that the expected returns of the two types of options are both below the risk-free rate (which is 0.21% per month), supporting Coval and Shumway (2001). Moving on to the components of the expected return, the expected payoff and value, columns (2) and (5) indicate that American puts are always more highly valued than their European counterparts, in line with Merton's (1973) insight that an American option's value equals the equivalent European option's value plus the value of the right to early exercise. Novel to the literature, columns (1) and (4), however, illustrate that the expected payoffs of American puts are, in proportional terms, even further above those of their European counterparts than their values, explaining why the early exercise risk premium is almost always positive in Table 1.

[10]The negative time-to-maturity effect on the optimal early exercise probability arises since the optimal early exercise threshold monotonically increases over the time-to-maturity (see Jacka (1991)). Conversely, the usually negative asset volatility effect arises since an option is optimally early exercised when the early exercise payoff exceeds the value of the alive option. A higher asset volatility, however, only raises the option value but not the early exercise payoff, making an immediate optimal early exercise less likely. Crucially, however, the optimal early exercise probability-asset volatility relation can switch sign for deeper OTM options with a longer time-to-maturity since while a higher asset volatility still lowers the chance of an immediate optimal early exercise it raises the chance of the option moving ITM over the remaining maturity time.

2.2.3 The Theoretical *Delta-Hedged* Early Exercise Risk Premium

Table 2 studies how stochastic volatility and asset-value jumps influence the early exercise risk premium, contrasting the GBM-world premiums with those in the SV and SVJ worlds (Panels A, B, and C, respectively). For convenience, Figure 2 plots the *delta-hedged* early exercise risk premiums in the SV and SVJ worlds, calculated as the differences between the Panel B or C entries in the table and the corresponding Panel A entries.[11]

Table 2 About Here

Both stochastic volatility and asset-value jumps exert direct and indirect effects on the premium. While the direct effects come from them changing the asset value's trajectory over the maturity time, the indirect come through their risk premiums. To better grasp the direct effects, consider a deep ITM (OTM) put on a low volatility asset in a GBM world. Allowing for stochastic volatility and/or jumps in such a situation is bad (good) news for the put owner since it enables the put to still move OTM (ITM), inducing the owner to speed up (delay) early exercising to mitigate (facilitate) that possibility. As a result, the early exercise risk premium rises (drops). To better grasp the indirect effects, recall that puts are well suited to hedge against variance and asset-value jump risks when these risks are negatively priced (as in our SV and SVJ worlds). The reason is that puts pay off when the underlying asset's value is low, stochastic volatility tends to be high, jumps are more likely to occur and tend to be more negative, and marginal utility tends to be high. In turn, the hedging ability of puts induces their owners to delay early exercising, lowering the early exercise risk premium.

Table 2 and Figure 2 show that the negative effects on the early exercise risk premium coming from the negative variance and jump risk premiums almost always dominate possibly positive

[11] Bakshi and Kapadia (2003) prove that the expected returns of delta-hedged American and European puts are zero in the GBM world. As a result, the delta-hedged early exercise risk premium is also zero in that world. Conversely, the delta-hedged premium picks up the differential effects of stochastic volatility and asset-value jumps on the expected returns of the two types of options in the SV and SVJ worlds, enabling us to calculate it as the raw premium in those worlds minus the raw premium in the GBM world.

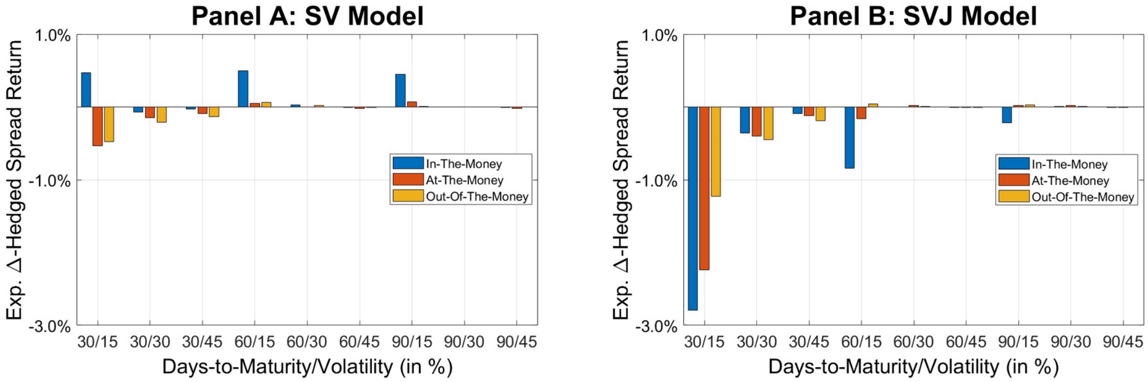

Figure 2: The Delta-Hedged Early Exercise Risk Premium The figure shows delta-hedged early exercise risk premiums in the SV (Panel A) and SVJ (Panel B) worlds across various puts. We calculate the delta-hedged premium as the raw premium in the SV or SVJ worlds in Panels B and C of Table 2 minus the corresponding raw premium in the GBM world in Panel A of that table, all respectively. The blue, red, and yellow bars signal in-the-money (strike-to-stock price: 1.05), at-the-money (1.00), and out-of-the-money (0.95) puts, respectively. The first number on the x-axis gives the days-to-maturity, and the second the annualized underlying-asset volatility. We describe the basecase parameter values in Section 2.2.1.

effects coming from changes in the underlying asset value's trajectory. This is particularly true in the SVJ world since our simulations include small but frequent jumps and we offset the additional volatility created by them through lowering long-run (and thus current) diffusive volatility (see Section IA.2 of the Internet Appendix for more intuition). The upshot is that the delta-hedged early exercise risk premium is typically negative but an order of magnitude smaller than the raw premium. In line with our arguments above, the single exception are ITM puts on extremely low volatility assets (i.e., $\sqrt{V(t)} = 0.15$) in the SV world. Since the hedging ability of puts is close to constant across moneyness in the SV world, the figure reveals that the effects coming from changes in the trajectory leads the delta-hedged premium to be the least (most) negative for ITM (OTM) puts in that world. In contrast, since direct jump effects hardly matter and the hedging ability of puts is greater for deeper ITM puts in the SVJ world, that same premium is more negative for ITM than OTM puts in that world.

More directly looking into the effects of moneyness, time-to-maturity, and asset volatility on the delta-hedged early exercise risk premium, Figure 2 suggests that, aside from puts on extremely low volatility assets, the delta-hedged premium is not strongly related to moneyness but rises toward zero with time-to-maturity and asset volatility. Conversely, looking into puts on extremely low volatility assets, the delta-hedged premium becomes more (less) negative with moneyness in the SV (SVJ) world but still rises toward zero with the other factors.

In the Internet Appendix, we further evaluate how variations in the SV and SVJ process parameters affect the early exercise risk premium. In accordance with our former conclusions, Tables IA.1 and IA.2 in that appendix suggest that those parameters condition the strengths of the direct and indirect effects outlined above, in turn affecting the premium in the anticipated ways. In that same appendix, we also assess whether our conclusions about the premium continue to hold for stock indexes, repeating our simulation exercise using the SV and SVJ process parameter values of Bates (2000), Eraker (2004), Broadie et al. (2009), Hurn et al. (2015), and Jacobs and Liu (2019). Tables IA.3 and IA.4 in that appendix illustrate that, if anything, the stock-index premium is more positive than the single-stock premium.

Overall, this section establishes that the early exercise risk premium in single-stock puts is typically positive and economically large in neoclassical models. Moreover, the premium strongly rises with moneyness and falls with time-to-maturity and asset volatility. Conversely, the delta-hedged early exercise risk premium is generally negative but an order of magnitude smaller than the raw premium. While the delta-hedged premium has an ambiguous relation with moneyness, it rises toward (moves away from) zero with time-to-maturity and asset volatility (more negative variance and jump risk premiums).

3 Main Cross-Sectional Evidence

In this section, we use cross-sectional tests to estimate the raw and delta-hedged early exercise risk premium in single-stock puts and to determine its relations with put and stock characteristics. In doing so, we first introduce our data sources and filters. We next detail our return calculations. We finally present the results from portfolio sorts and FM regressions.

3.1 Data Sources and Filters

We obtain daily data on American calls and puts written on single stocks with no payouts over their maturity times ("zero-dividend stocks"), the stocks underlying the options, and interest rates from Optionmetrics. We source additional market and firm-fundamental data on those same stocks from CRSP and Compustat, respectively. We retrieve data on stock short-sale constraints from Markit. Our sample period is January 1996 to December 2021.

We impose standard filters on our options data. To wit, we drop option-day observations for which the option price violates standard arbitrage bounds (as, e.g., that an American call's price must lie between $\max(0, \text{equivalent long forward value})$ and the stock price) or does not exceed one-half the option bid-ask spread. We further drop observations for which the option bid-ask spread is negative or the stock price is missing. To mitigate microstructure biases, we exclude options with a time value below one dollar at the start of the return horizon.

3.2 Calculating Single-Stock Put Returns

We rely on sold-before-maturity calendar-month put returns in our main empirical tests. In particular, we calculate an American put's raw return as the ratio of its early exercise payoff compounded to the month end (if there is an optimal early exercise during the month) or its end-month price (if there is none) to its start-month price. We identify optimal early exercises using Barraclough and Whaley's (2012) "market rule," comparing the daily early exercise payoff with the daily price over the month. While we would ideally assume that an early exercise occurs the first time the payoff is greater than or equal to the price, we cannot do so in practice since, in the absence of arbitrage opportunities, the payoff cannot exceed the price, while, under minimum tick size rules, it also cannot be equal to the price. To overcome that problem, we assume that an early exercise occurs if the early exercise payoff comes sufficiently close to the put price. More rigorously, we assume that an early exercise occurs if:

$$\frac{P^A(t) - \max(K - S(t), 0)}{\max(K - S(t), 0)} \leq 0.05, \tag{4}$$

where $P^A(t)$ is the American put's price and $\max(K - S(t), 0)$ its early exercise payoff at the end of day t. While an upside of our identification strategy is that it does not rely on a possibly misspecified option pricing model, a downside is that it may slightly overstate the number of optimal early exercises in the data. Internet Appendix Table IA.5 gives simulation evidence suggesting that our identification strategy does not greatly bias our empirical results.[12]

We calculate a European put's return as the ratio of its end-month price to its start-month price. In doing so, we face the issue that U.S. options exchanges only trade American (and not European) single-stock options. To overcome that problem, we synthetically create single-stock European puts from the put-call parity relation. More specifically, we start from Merton's (1973) insight that it is never optimal to early exercise American calls written on zero-payout assets. Given that our sample data contain only options on zero-dividend stocks, it follows that our sample American calls are equivalent to European calls. We next recall that we can replicate a European put through longing the equivalent European call, shorting the underlying stock, and investing the discounted strike price into the money market:

$$P^{SE}_{i,K,T}(t) = C^A_{i,K,T}(t) - S_i(t) + Ke^{-r_f(T-t)}, \tag{5}$$

where $P^{SE}_{i,K,T}(t)$ is the time-t price of a synthetic European put on stock i and with strike price K and maturity date T, $C^A_{i,K,T}(t)$ is the price of the equivalent exchange-traded American call, $S_i(t)$ is stock i's price, and r_f is the risk-free rate of return over the maturity time.

Whenever possible, we impose the same filters as those above on the synthetic European put

[12] Our empirical evidence is robust to changing the threshold in Equation (4) to 0.01 or 0.02.

prices to ensure that the exchange-traded and synthetic option prices are similarly clean. To be specific, we again drop put-month observations for which the synthetic European put price violates standard arbitrage bounds. Moreover, we also omit both the American and European put price if the American put price does not exceed the European put price. To be consistent with the exchange-traded option prices, we finally also exclude synthetic European puts with a time value below one dollar at the start of the return horizon.[13]

To verify that our synthetic European put returns are reasonably non-biased and accurate, Table 3 reports the results from subsample panel regressions of them on their corresponding never-early-exercised American put returns, where the subsamples are formed from the time value of the American puts at the start of the return period. In line with the idea that a high time value implies a low optimal early exercise probability, the regressions suggest that the synthetic European put returns essentially converge to the American put returns with a higher time value. Critically, the subsample formed from American puts with a time value above \$10 yields a constant estimate of 0.01, a slope estimate of 1.04, and an R-squared of 95%.

TABLE 3 ABOUT HERE

We follow Bakshi and Kapadia (2003), Cao and Han (2013), and others in computing a put's delta-hedged return. In particular, we calculate its delta-hedged *payoff*, Π^x, as:

$$\Pi^x = P^x(t) - P^x(t-1) - \sum_{n=0}^{N-1} \Delta_{P^x,t_n}[S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}[P^x(t_n) - \Delta_{P^x,t_n} S(t_n)], \quad (6)$$

[13] While a few studies on raw options also consider held-to-maturity (in addition to sold-before-maturity) returns, we cannot do so for the same reason that studies on delta-hedged options cannot. The reason is that option prices become extremely inaccurate over their final days-to-maturity, with, for example, 98% (24%) of our sample options violating basic arbitrage bounds one (ten) day(s) before maturity (see our Internet Appendix). While the inaccurate prices shortly before maturity are no problem for the raw-option studies since they calculate the option payoff from the stock (and not option) price, we (the delta-hedged-option studies) require accurate prices over the entire return horizon to precisely identify optimal early exercises (to have reliable option deltas). Notwithstanding, Tables IA.6 and IA.7 in our Internet Appendix reveal that "almost-held-to-maturity returns" obtained from options sold one week before maturity also support our theoretical predictions.

where $x \in \{A, SE\}$ indicates the American (A) or synthetic European (SE) put, $P^x(t)$ is the payoff of the put at the end of the investment horizon (the numerator of its raw return), and $P^x(t-1)$ its price at the start of that horizon (the denominator of its raw return). Conversely, $t_n \in \{t_0, t_1, \ldots, t_{N-1}\}$ denotes the trading days within the investment period (so that $t_0 = t-1$ and $t_N = t$), Δ_{P^x,t_n} is the put's delta at the end of trading day t_n, and $S(t_n)$ is the underlying stock's price at the end of that same day.[14] Finally, a_n is the day count from trading day t_n to the next, and $r(t_n)$ is the net annual interest rate at the end of day t_n. While the first summand, $P^x(t) - P^x(t-1)$, gives the put's payoff, the second, $\sum_{n=0}^{N-1} \Delta_{P^x,t_n}[S(t_{n+1}) - S(t_n)]$, offers the payoff from the stock replication portfolio, and the third, $\sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}[P^x(t_n) - \Delta_{P^x,t_n} S(t_n)]$, the cost from financing the delta-hedged position. We highlight that Equation (6) assumes that the delta-hedged American put position is liquidated upon an optimal early exercise. We finally calculate the delta-hedged put return as the ratio of the delta-hedged payoff to the absolute initial value of the delta-hedged position (i.e., $\text{abs}(P^x(t_0) - \Delta_{P^x,t_0} S(t_0))$).

We match the American and synthetic European put data along the underlying stock, strike price, and maturity time dimensions, ensuring that each American put with non-missing data corresponds to exactly one synthetic European put with non-missing data.

3.3 The Empirical Early Exercise Risk Premium

3.3.1 The Unconditional Raw Premium

We first take a look at the unconditional early exercise risk premium in our sample data. To that end, Table 4 presents descriptive statistics for the monthly returns of optimally and never early-exercised American (columns (1) and (2)) and synthetic European ((3)) puts, the spreads across these ((1)–(3), (1)–(2), and (2)–(3)), and their moneyness and days-to-maturity at the start of the return period ((4) and (5)), all respectively. While we focus on the raw put returns

[14] We use the Optionmetrics American put delta for the American put and one minus the Optionmetrics American call delta for the synthetic European put, as implied by put-call parity.

in Panel A in this section, we return to the delta-hedged returns in Panel B later. We define moneyness as the ratio of the strike price to the underlying stock's price. With the exception of the t-statistic and its 95% confidence interval, we compute all statistics first by sample month and then average over our sample period. Since there could be concern that standard asymptotic inference levels are biased for options (see Broadie et al. (2009)), we follow Vasquez (2017) in using a bootstrap to create the confidence interval. We offer more details about that bootstrap as well as others used later in Appendix A in this paper.

Table 4 About Here

In line with our theory, Table 4 suggests that the early exercise risk premium in puts is positive in our sample data. Realizing that we can interpret the means in columns (1) to (3) as the mean returns of equally-weighted portfolios, the table reveals that both *optimally-early-exercised* American and European puts yield significantly negative mean returns. Despite that, the American puts yield a less negative mean return of –7.69% per month (t-statistic: –3.33) compared to the mean return of European puts of –10.07% (t-statistic: –4.21). The upshot is that the spread in mean returns across those option types is 2.38% (t-statistic: 5.58; see column (1)–(3)), not only far outside its 95% confidence interval but also, remarkably, more statistically significant than the mean returns of the underlying puts.

We next evaluate whether our results would change if we did not allow for optimal early exercises in our American put return calculations. The table suggests that *never-early-exercised* American puts yield a mean return of –10.96% per month (t-statistic: –4.99), not only strikingly different from the mean return of optimally-early-exercised American puts of –7.69% but also below (not above) the mean European put return of –10.07% (see column (2)). The implication is that the spread in mean returns becomes a negative –0.89% (t-statistic: –3.75) upon not allowing for such exercises (see column (2)–(3)). The switch in the sign of the spread aligns with evidence that American puts have higher prices than equivalent European puts (see

Zivney (1991), de Roon and Veld (1996), etc.), implying that those options necessarily have lower mean returns in the absence of early-exercise-induced higher mean payoffs.

3.3.2 The Raw Premium and Put and Stock Characteristics

We now evaluate our theoretical predictions that the early exercise risk premium rises with moneyness but falls with time-to-maturity and underlying-asset volatility. Starting with double portfolio sorts based on moneyness and time-to-maturity, we split the American (alternatively: European) puts into an ITM (strike-to-stock price above 1.05), an ATM (0.95-1.05), and an OTM (below 0.95) portfolio at the end of each sample month $t-1$. We next independently split them into portfolios according to whether their days-to-maturity lie between 30 and 60, 60 and 90, and 90 and 120 days at that time. We use the intersection of the univariate portfolios to create double-sorted portfolios. We equally-weight[15] the double sorted portfolios, also forming spread portfolios long one of the American put portfolios and short the corresponding European put portfolio. We finally calculate portfolio returns over month t, separately considering the optimally-early-exercised or never-early-exercised American put return cases.

Table 5 presents the results from the double-sorted portfolio exercise. The plain numbers are the mean monthly portfolio returns, whereas the numbers in square brackets are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate statistical significance at the bootstrapped 99%, 95%, and 90% confidence level, respectively. While Panels A, B, and C focus on the ITM, ATM, and OTM puts, the upper, middle, and lower rows in each panel focus on the short, medium, and long time-to-maturity puts, all respectively. Supporting our theory, the table shows that the early exercise risk premium rises with moneyness but falls with time-to-maturity. Allowing for optimal early exercises, the mean spread return of 30-60 day puts, for example, rises from a mildly significant 1.57% (t-statistic: 1.88) for OTM puts to

[15]Tables IA.8 and IA.9 in our Internet Appendix demonstrate that value-weighted (i.e., option-price-weighted) double-sorted moneyness and time-to-maturity and univariate idiosyncratic stock volatility portfolios yield results in complete agreement with those from the equally-weighted portfolios.

a highly significant 6.29% (t-statistic: 6.65) for ITM puts (see column (1)–(3)). Conversely, the mean spread return of ATM puts rises from an insignificant 0.21% (t-statistic: 1.12) for 90-120 day puts to 4.47% (t-statistic: 6.26) for 30-60 day puts (see same column).

TABLE 5 ABOUT HERE

Noteworthily, column (2)–(3) in the same table suggests that the effects of moneyness and time-to-maturity on the early exercise risk premium either greatly attenuate or completely disappear upon us not allowing for optimal early exercises. The mean spread return of the 30-60 day puts, for example, now rises by a mere 2.08% (compared to 4.73% before) over the low-to-high moneyness portfolios, while the same return of the ATM puts now rises by a mere 0.21% (compared to 4.26% before) over the long-to-short maturity time portfolios.

We next split the American (alternatively: European) puts into quintile portfolios according to idiosyncratic stock volatility at the end of each sample month $t-1$. We use the standard deviation of the residual from the Fama-French (1993)-Carhart (1997; FFC) model calibrated to daily data over the prior twelve months as volatility estimate. To avoid distorting effects arising from sufficiently OTM puts yielding a positive early exercise risk premium-asset volatility relation (see Section 2.2.2), we also independently sort those same puts into quintile portfolios according to the strike-to-stock price ratio ("moneyness") at that time. We use the intersection of those sorts to create equally-weighted double-sorted portfolios. We finally form volatility portfolios *controlling for moneyness* by creating equally-weighted portfolios of those portfolios within one volatility class. We further form spread portfolios long an American and short the equivalent European put volatility portfolio plus long the top and short the bottom volatility portfolio from the moneyness-controlled portfolios. We hold all portfolios over month t.

Table 6 offers the univariate portfolio exercise results, studying optimally-early-exercised and never-early-exercised American puts in Panels A and B, respectively. Again in line with our theory, the table suggests that the early exercise risk premium drops with idiosyncratic stock volatility. Allowing for optimal early exercises, Panel A reports that the mean spread return across equivalent American and European puts drops from 4.39% (t-statistic: 7.37) to –0.35% (t-statistic: –0.66) over the low-to-high volatility portfolios. The difference is a highly significant –4.74% (t-statistic: –9.01). The same difference is greatly attenuated upon us not allowing for such exercises, with it changing to –1.86% (t-statistic: –4.74; see Panel B). The final row confirms that the volatility portfolios are close-to-identical in terms of their average moneyness.[16]

Table 6 About Here

In Table 7, we switch to FM regressions using the spread return between equivalent American and European puts over month t as dependent variable and combinations of moneyness, time-to-maturity (as fraction of a year), and annual FFC idiosyncratic stock volatility as independent variables. While we account for optimal early exercises in our calculations in Panel A, we do not do so in Panel B. The FM regressions yield results in complete agreement with the portfolio sorts. Allowing for optimal early exercises, Panel A shows that the spread return between the equivalent puts rises in moneyness and drops in time-to-maturity and volatility at significant levels. Conversely, not allowing for such exercises, Panel B demonstrates that the relation of the spread return with time-to-maturity becomes insignificant, while its relations with moneyness and volatility become far more attenuated compared to before.

Table 7 About Here

3.3.3 The Raw Premium and the Interest Rate

We also test the theoretical prediction that the early exercise risk premium declines to zero with the risk-free rate dropping to the same number. We can easily understand that prediction from Carr et al.'s (1992) American put replication strategy, realizing that when the risk-free

[16]In unreported tests, we also form double-sorted moneyness and idiosyncratic stock volatility portfolios. In line with our simulation evidence, those portfolios suggest that the early exercise risk premiums drop more strongly with stock volatility for higher rather than lower moneyness puts.

rate is zero, the American put no longer yields incremental payoffs compared to its equivalent European put and thus becomes equivalent to that European put. To test that prediction, we rely on the sudden drop in the annual risk-free rate from an average of 3.59% until the start of 2008 to an average of 0.44% thereafter as exogenous shock, treating American puts with a high (low) optimal early exercise probability as treated (control) puts.

Internet Appendix Table IA.10 supports the conjecture that the early exercise risk premium of especially ITM puts decreases with drops in the risk-free rate. For example, while the mean spread return of optimally-early-exercised 60-90 day ITM puts drops by a significant 3.88% per month (t-statistic: –5.02) from the earlier (high risk-free rate) to the later (low risk-free rate) subperiod, the corresponding number for otherwise identical OTM puts is an only insignificant 0.15% (t-statistic: –0.20) over that same period. Conversely, looking into never-early-exercised American puts, we find much weaker and often insignificant changes.

3.3.4 The Unconditional and Conditional Delta-Hedged Premium

We finally look into the delta-hedged early exercise risk premium in our sample data. To do so, we first return to Panel B of Table 4, suggesting that, in line with the literature, both optimally-early-exercised American and European puts yield negative mean delta-hedged returns. Notwithstanding, while the American puts yield a significant mean return of –0.74% per month (t-statistic: –5.21), the corresponding number for European puts is a much higher and insignificant –0.24% (t-statistic: –1.47). The upshot is that the delta-hedged early exercise risk premium is a significant –0.50% (t-statistic: –12.20), corroborating the idea that negative variance and/or jump risk premiums induce American put owners to delay early exercising their positions (see column (1)–(3)). Switching from the optimally-early-exercised to the never-early-exercised American puts, column (2)–(3) shows that the delta-hedged premium becomes much weaker but remains significant (estimate: –0.22%; t-statistic: –9.36).

We next study how put or stock characteristics condition the delta-hedged early exercise risk premium. We start with repeating the double portfolio sorts based on moneyness and time-to-maturity in Table 5 using delta-hedged puts. Consistent with our SVJ (but not SV) simulation evidence in Figure 2,[17] Table 8 suggests that the delta-hedged premium does not vividly relate to moneyness but rises toward zero with time-to-maturity. Considering 30-day optimally-early-exercised puts, the monthly delta-hedged premium is, for example, –0.74%, –0.50%, and –0.70% for ITM, ATM, and OTM puts (t-statistics: –15.21, –12.38, and –9.62), all respectively. Conversely, considering optimally-early-exercised OTM puts, the same premium is –0.70%, –0.44%, and –0.34% for 30, 60, and 90 day puts (t-statistics: –9.62, –9.67, and –9.17), all respectively (see Panel C). Noteworthily, not allowing for optimal early exercises, the delta-hedged premium markedly drops with both moneyness and time-to-maturity.

TABLE 8 ABOUT HERE

We finally repeat the univariate idiosyncratic stock volatility portfolio exercise controlling for moneyness in Table 6 using delta-hedged put returns. In case of these portfolios, we, however, follow the delta-hedged option literature in interpreting a stock's volatility as an inverse proxy for its variance risk premium (see also Equation (3)). As discussed in Section 2.2.3 and more explicitly shown in our Internet Appendix, a more negative variance risk premium should make the delta-hedged early exercise risk premium more negative since it incentivizes put owners to avoid early exercising to not eliminate the puts' ability to hedge against variance risk. Table 9 confirms this assertion, showing that the delta-hedged premium drops with a more negative variance risk premium. Allowing for optimal early exercises, Panel A reveals that the monthly delta-hedged premium is –0.37% for puts on the lowest volatility (mild variance risk) stocks but –0.80% for those on the highest volatility (high variance risk) stocks, with the spread equal

[17] More specifically, while Panel A of Figure 2 shows that the delta-hedged premium drops with moneyness for each maturity time-asset volatility pair in the SV world, Panel B reveals that it rises with moneyness for low-asset-volatility pairs but (mildly) drops with moneyness for higher-volatility pairs. In sum, the SVJ world is thus more likely to produce a flat relation between the delta-hedged premium and moneyness.

to –0.44% (t-statistic: –8.70). Conversely, not allowing for such exercises, Panel B reports that the same spread becomes a less negative –0.28% (t-statistic: –5.67).

TABLE 9 ABOUT HERE

3.3.5 Robustness Tests

We conduct several robustness tests in our Internet Appendix. We first address the concern that violations of the rule to never optimally early exercise an American call on a zero-dividend stock and/or of put-call parity induced through short-sale constraints and/or stock or option illiquidity drives our evidence (see Cremers and Weinbaum (2010), Jensen and Pedersen (2016), and Figlewski (2022)). To that end, Table IA.11 shows that excluding put pairs on short-sale constrained stocks amplifies our early exercise risk premium estimates, whereas Table IA.12 reveals that also excluding those pairs involving an illiquid stock, American call, or American put further amplifies them. We next turn to the concern that investors' inability to identify zero-dividend stocks drives our evidence. To that end, Table IA.13 reports that only including put pairs on stocks projected to not pay out dividends hardly affects our estimates. Table IA.14 finally shows that incorporating the realistic transaction costs of Muravyev and Pearson (2020) does not eliminate our positive early exercise risk premium estimates for short time-to-maturity ITM/ATM puts, suggesting that real world investors can earn these premiums.

Taken together, this section establishes that the empirical early exercise risk premium in single-stock puts is positive and economically meaningful, rises with moneyness and falls with time-to-maturity and stock volatility, and is stronger in high interest rate states. Conversely, the empirical delta-hedged premium is negative, is economically meaningful, is flat in moneyness, and becomes less negative with time-to-maturity but more negative with a more pronounced variance risk premium. Critically, our results in this section only arise/are much stronger when we allow for optimal early exercises in our American put return calculations.

4 Replication Exercise

In this section, we assess the implications of our early exercise risk premium conclusions for existing cross-sectional option return studies. We start with introducing the existing studies and explaining how we replicate them, either allowing or not allowing for optimal early exercises in return calculations. We then offer the results from our replication exercise.

4.1 Option Anomaly Choice and Methodology

We choose 15 well-known option return anomalies from twelve studies for our replication exercise, showing the anomalies as well as the studies in Table 10.[18] Most prominently, the anomalies include Goyal and Saretto's (2009) realized-to-implied volatility, Cao and Han's (2013) idiosyncratic stock volatility, Boyer and Vorkink's (2014) option skewness, and Frazzini and Pedersen's (2022) embedded leverage anomalies. We next exactly recalculate the anomaly variables as in the studies (see the column titled "variable definition"). Separately using each of the anomaly variables, we sort the same options as in the studies (single-stock American puts, single-stock American straddles, or delta-hedged single-stock American puts with the same moneyness (usually ATM) and time-to-maturity (usually short) as in the original studies;[19] see the column titled "return type") into equally-weighted quintile portfolios at the end of each sample month $t-1$.[20] We then form a spread portfolio long the top and short the bottom quintile portfolio and hold it over month t. Critically, we separately calculate the returns of all American puts underlying the spread portfolios allowing or not allowing for optimal early exercises.

Table 10 About Here

[18]To be concise, we choose only one of Zhan et al.'s (2022) three financing anomaly variables and only one of their three profitability variables. Our evidence obtained from the omitted financing and profitability variables aligns with those obtained from the included variables.

[19]Our sample straddles are portfolios long both the equivalent American calls and puts. Just like in case of the delta-hedged American puts, we liquidate the entire position upon an optimal early exercise.

[20]Our empirical conclusions are robust to sorting into equally-weighted decile portfolios.

While we run the replication exercise over our updated sample period ending in December 2021, we stress that we obtain close-to-identical conclusions if we rely on the (often greatly outdated) sample periods used in the original studies (see the column titled "original sample period" in Table 10). We further highlight that since there are no mutually-agreed-upon sets of risk factors in the cross-sectional option return literature, and since the risk factors used in the studies in that literature hardly ever affect their conclusions, we decided, for the sake of simplicity, to not control for risk factors in our replication exercise.

4.2 Optimal Early Exercises and Option Anomalies

Table 11 offers the results from the replication exercise. While column (1) shows the mean spread portfolio returns of the anomalies upon us not allowing for optimal early exercises (so that the column directly replicates the anomaly studies), column (2) reports those same returns upon us allowing for such exercises. In turn, columns (2)–(1) and (3) offer the (signed) differences across the two cases and the absolute percentage changes from the first to the second (i.e., the absolute difference scaled by the absolute earlier mean return), respectively. In Panels A to C, we focus on the raw put, straddle, and delta-hedged put anomalies, respectively.

TABLE 11 ABOUT HERE

The table strongly suggests that allowing for optimal early exercises has an economically large effect on the option anomalies. Starting with our calculations not allowing for optimal early exercises (and thus the direct replications), column (1) shows that all 15 anomalies still exist over our updated sample period, with their mean spread portfolio returns continuing to be highly significant with the expected sign.[21] The survival of the anomalies is noteworthy since we often rely on a much longer sample period than the replicated studies. Even more strikingly, column (2) reveals that allowing for optimal early exercises greatly changes the

[21]The exception is Zhan et al.'s (2022) share issuances anomaly which is only marginally significant.

mean spread portfolio returns, with column (2)–(1) establishing that the change is significant at the 95% (99%) confidence level in 14 (13) cases. In turn, column (3) demonstrates that the change is not only statistically but also economically important, with the average absolute percent change equal to 32% and the largest such change equal to 53%. In line with the insight that the sign of the change depends on whether high early-exercise-probability puts cluster in the top or bottom portfolio, the anomaly becomes more (less) pronounced in nine (five) out of the 14 significant-change cases. Perhaps most remarkably, column (2) indicates that, in each case in which an anomaly becomes less pronounced, that same anomaly is no longer significant at the 95% confidence level upon us allowing for optimal early exercises.

As illustrative examples, while Hu and Jacobs's (2020) total volatility raw-put anomaly yields a highly significant mean return of 9.30% (t-statistic: 3.53) upon us not allowing for optimal early exercises, that same return becomes an insignificant 5.06% (t-statistic: 2.03) upon us doing so. In the same vein, the mean return of Frazzini and Pedersen's (2022) delta-hedged-put moneyness anomaly changes from a significant 2.09% (t-statistic: 2.72) to an insignificant 1.34% (t-statistic: 1.77) upon us allowing for such exercises. As an opposite example, while Vasquez's (2017) implied volatility slope straddle anomaly yields a highly significant mean return of 2.88% (t-statistic: 4.43) upon us not allowing for optimal early exercises, that same return becomes an even more significant 4.01% (t-statistic: 6.67) upon us doing so.

Overall, this section shows that allowing for optimal early exercises greatly affects the profitability of existing option anomalies. Despite that, it further reveals that unless we know how an anomaly variable relates to the optimal early exercise probability, it is often hard to assess whether allowing for such exercises amplifies or dampens the anomaly.

5 Concluding Remarks

We study how the ability to optimally early exercise a plain-vanilla put affects its expected raw and delta-hedged returns, contrasting those returns across equivalent American and European puts. On the theoretical front, we show that the expected raw return spread ("the early exercise risk premium") is positive and economically large and rises with moneyness but falls with time-to-maturity and asset volatility. Conversely, the expected delta-hedged-return spread ("the delta-hedged premium") is negative and economically meaningful, is flat in moneyness, rises with time-to-maturity and asset volatility, and drops with a more negative variance and/or jump risk premium. On the empirical front, a comparison of optimally-early-exercised American puts, never-early-exercised American puts, and synthetic European puts derived from put-call parity supports our theoretical predictions. Moreover, allowing for optimal early exercises in the replication of 15 well-known option return anomalies significantly changes the profitability of those anomalies, with five anomalies becoming statistically insignificant.

A Bootstrap Details

This appendix offers more details about the construction of the bootstrapped confidence intervals for the t-statistics of mean portfolio returns and FM regression estimates.

A.1 Bootstrapping Mean Portfolio Returns

Starting with the mean portfolio returns, we first impose the null hypothesis of a zero mean on the relevant time-series of portfolio returns. We next draw with replacement and equal drawing probability 312 portfolio returns from that time-series, where 312 is the total number of months in our sample data. We then employ the drawn returns to compute a bootstrapped t-statistic. Repeating these steps 20,000 times, we finally choose the 0.5th (2.5th) [5th] and 99.5th (97.5th) [95th] percentiles of the bootstrapped t-statistic distribution as upper and lower limit of the bootstrapped 99% (95%) [90%] confidence interval for the t-statistic.

A.2 Bootstrapping FM Regression Estimates

Turning to the FM estimate on some independent variable in some model, we first estimate all cross-sectional regressions in our sample period and impose the null hypothesis by recreating the dependent variable through adding the fitted regression value excluding the summand involving the independent variable, and the residual. We next resample each cross-section, drawing with replacement and an equal drawing probability a number of observations for the bootstrapped dependent variable and the associated independent variables equal to that in the original cross-section. We finally run the FM estimation on the resampled data, yielding a bootstrapped t-statistic for the estimate of the independent variable. Repeating those steps 1,000 times, we are again able to calculate the lower and upper limits of the 99%, 95%, and 90% confidence intervals from the distribution of the bootstrapped t-statistic.

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Table 1: The Early Exercise Risk Premium in a GBM World

The table presents the expected payoff, value, and expected raw return of equivalent American (columns (1) to (3)) and European ((4) to (6)) puts as well as the differences in these statistics across those put types (remaining columns), all respectively. Panels A to C consider in-the-money (strike-to-stock price = 1.05), at-the-money (1.00), and out-of-the-money (0.95) puts. Within each moneyness class, we further consider puts with 30, 60, and 90 days-to-maturity. Within each maturity class, we finally consider puts on an asset with an annualized volatility of 15%, 30%, and 45%. Each simulation relies on five million asset-value paths with a number of time steps equal to the days-to-maturity. We describe the basecase parameter values in Section 2.2.1.

		American Put			European Put			American−European		
Days to Mat.	Vol. (%)	Expected Payoff	Value	Expected Return (%)	Expected Payoff	Value	Expected Return (%)	Expected Payoff	Value	Expected Return (%)
		(1)	(2)	(3)	(4)	(5)	(6)	(1)−(4)	(2)−(5)	(3)−(6)
Panel A: In-The-Money (Strike-to-Stock Price = 1.05)										
30	15	2.43	2.58	−5.97	2.22	2.55	−12.79	0.20	0.03	6.82
	30	3.04	3.22	−5.69	2.95	3.22	−8.13	0.08	0.00	2.45
	45	3.84	4.02	−4.34	3.79	4.02	−5.78	0.06	0.00	1.43
60	15	2.53	2.75	−8.03	2.43	2.71	−10.45	0.10	0.04	2.43
	30	3.60	3.82	−5.59	3.58	3.81	−6.04	0.03	0.01	0.45
	45	4.80	5.00	−3.92	4.79	5.00	−4.12	0.01	0.00	0.20
90	15	2.67	2.92	−8.30	2.59	2.86	−9.22	0.08	0.06	0.92
	30	4.07	4.29	−5.00	4.05	4.27	−5.08	0.02	0.02	0.08
	45	5.56	5.75	−3.36	5.55	5.75	−3.39	0.01	0.01	0.03
Panel B: At-The-Money (Strike-to-Stock Price = 1.00)										
30	15	0.67	0.82	−17.51	0.64	0.81	−21.17	0.03	0.00	3.66
	30	1.53	1.68	−8.78	1.50	1.68	−10.61	0.03	0.00	1.83
	45	2.39	2.53	−5.74	2.36	2.53	−6.94	0.03	0.00	1.20
60	15	0.97	1.13	−14.58	0.95	1.12	−15.05	0.01	0.01	0.47
	30	2.17	2.34	−7.14	2.17	2.34	−7.33	0.01	0.00	0.19
	45	3.39	3.55	−4.60	3.39	3.55	−4.72	0.00	0.00	0.12
90	15	1.19	1.36	−12.42	1.17	1.34	−12.47	0.02	0.02	0.04
	30	2.67	2.84	−5.96	2.66	2.83	−5.97	0.01	0.01	0.01
	45	4.15	4.32	−3.78	4.15	4.31	−3.80	0.00	0.00	0.02
Panel C: Out-Of-The-Money (Strike-to-Stock Price = 0.95)										
30	15	0.08	0.11	−30.26	0.08	0.11	−32.05	0.00	0.00	1.79
	30	0.61	0.69	−12.22	0.60	0.69	−13.61	0.01	0.00	1.39
	45	1.33	1.43	−7.28	1.31	1.43	−8.30	0.01	0.00	1.02
60	15	0.24	0.30	−20.78	0.23	0.30	−20.79	0.00	0.00	0.01
	30	1.16	1.27	−8.78	1.16	1.27	−8.83	0.00	0.00	0.05
	45	2.25	2.38	−5.34	2.25	2.38	−5.40	0.00	0.00	0.06
90	15	0.39	0.47	−16.45	0.39	0.46	−16.43	0.00	0.00	−0.03
	30	1.60	1.73	−7.00	1.60	1.72	−6.99	0.00	0.00	−0.01
	45	2.97	3.10	−4.25	2.97	3.10	−4.24	0.00	0.00	0.00

Table 2: The Early Exercise Risk Premium in Alternative Worlds

The table presents the expected raw returns of equivalent American and European puts as well as the differences in these statistics across the two put types under alternative stochastic processes used to model the value of the underlying asset. The alternative stochastic processes consist of a geometric Brownian motion (GBM) process (Panel A; repeated for convenience), a stochastic volatility (SV) process (Panel B), and a stochastic volatility-jump (SVJ) process (Panel C). Columns (1), (2), and (1)–(2) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (3), (4), and (3)–(4) at-the-money (ATM; 1.00), and columns (5), (6), and (5)–(6) out-of-the-money (OTM; 0.95) puts. Within each moneyness class, we consider puts with 30, 60, and 90 days-to-maturity. Within each maturity class, we finally consider puts on an asset with an annualized volatility of 15%, 30%, and 45%. Each simulation relies on five million asset-value paths with a number of time steps equal to the days-to-maturity. We describe the basecase parameter values in Section 2.2.1.

		Expected Net Option Return (in %)								
Days		ITM Puts			ATM Puts			OTM Puts		
to Mat.	Vol. (%)	American	European	Difference	American	European	Difference	American	European	Difference
		(1)	(2)	(1)−(2)	(3)	(4)	(3)−(4)	(5)	(6)	(5)−(6)
Panel A: Geometric Brownian Motion (GBM) Model										
30	15	−5.97	−12.79	6.82	−17.51	−21.17	3.66	−30.26	−32.05	1.79
	30	−5.69	−8.13	2.45	−8.78	−10.61	1.83	−12.22	−13.61	1.39
	45	−4.34	−5.78	1.43	−5.74	−6.94	1.20	−7.28	−8.30	1.02
60	15	−8.03	−10.45	2.43	−14.58	−15.05	0.47	−20.78	−20.79	0.01
	30	−5.59	−6.04	0.45	−7.14	−7.33	0.19	−8.78	−8.83	0.05
	45	−3.92	−4.12	0.20	−4.60	−4.72	0.12	−5.34	−5.40	0.06
90	15	−8.30	−9.22	0.92	−12.42	−12.47	0.04	−16.45	−16.43	−0.03
	30	−5.00	−5.08	0.08	−5.96	−5.97	0.01	−7.00	−6.99	−0.01
	45	−3.36	−3.39	0.03	−3.78	−3.80	0.02	−4.25	−4.24	0.00
Panel B: Stochastic Volatility (SV) Model										
30	15	−5.99	−13.27	7.28	−18.51	−21.63	3.12	−28.00	−29.31	1.31
	30	−6.33	−8.71	2.38	−9.90	−11.58	1.68	−13.79	−14.97	1.19
	45	−5.09	−6.49	1.40	−6.91	−8.02	1.11	−8.96	−9.84	0.88
60	15	−7.95	−10.88	2.93	−15.02	−15.54	0.52	−20.12	−20.20	0.07
	30	−5.89	−6.37	0.48	−7.60	−7.79	0.19	−9.36	−9.43	0.07
	45	−4.28	−4.47	0.19	−5.09	−5.19	0.10	−5.96	−6.01	0.05
90	15	−8.22	−9.60	1.37	−12.66	−12.78	0.12	−15.95	−15.93	−0.02
	30	−5.19	−5.27	0.08	−6.20	−6.21	0.01	−7.28	−7.27	−0.01
	45	−3.56	−3.58	0.02	−4.05	−4.04	0.00	−4.57	−4.57	0.00
Panel C: Stochastic Volatility-Jump (SVJ) Model										
30	15	−7.25	−11.28	4.03	−24.56	−25.98	1.42	−50.79	−51.35	0.56
	30	−6.73	−8.82	2.08	−11.82	−13.25	1.43	−19.30	−20.24	0.94
	45	−5.39	−6.73	1.34	−7.72	−8.80	1.09	−10.80	−11.63	0.83
60	15	−8.51	−10.10	1.59	−16.49	−16.80	0.31	−25.67	−25.72	0.05
	30	−6.23	−6.67	0.45	−8.41	−8.62	0.21	−11.13	−11.19	0.07
	45	−4.58	−4.77	0.19	−5.56	−5.67	0.11	−6.72	−6.77	0.05
90	15	−8.28	−8.98	0.70	−13.07	−13.14	0.06	−18.27	−18.26	0.00
	30	−5.33	−5.43	0.10	−6.60	−6.63	0.03	−8.12	−8.12	0.00
	45	−3.70	−3.71	0.02	−4.26	−4.26	0.00	−4.91	−4.90	−0.01

Table 3: Regressions of Synthetic European Put Returns on American Put Returns

The table presents the results of panel regressions of the raw return of a synthetic European put over month t on the raw return of the equivalent never-early-exercised American put over that same month separately estimated on time-value subsamples. We form the time-value subsamples according to whether the difference between an American put's price and its early exercise payoff at the start of the return period lies below \$0.50, between \$0.50 and \$1.00, between \$1.00 and \$2.00, between \$2.00 and \$4.00, between \$4.00 and \$10.00, and above \$10.00. In addition to the constant (column (1)) and slope coefficient ((2)) estimates, the table also reports the adjusted R-squared ((3)) and the number of observations ((4)) of each regression.

	Constant	Slope Coefficient	Adjusted R-Squared	Number of Observations
	(1)	(2)	(3)	(4)
$0.00 <$ Time Value ≤ 0.50	0.15	1.38	55.3%	197,844
$0.50 <$ Time Value ≤ 1.00	0.10	1.28	59.0%	67,389
$1.00 <$ Time Value ≤ 2.00	0.07	1.25	65.2%	72,277
$2.00 <$ Time Value ≤ 4.00	0.04	1.13	72.2%	47,089
$4.00 <$ Time Value ≤ 10.00	0.02	1.08	85.4%	29,520
Time Value > 10.00	0.01	1.04	95.1%	15,726

Table 4: Descriptive Statistics on Raw and Delta-Hedged Put Returns

The table presents descriptive statistics for the raw (Panel A) and delta-hedged (Panel B) monthly returns of optimally-early-exercised American puts (column (1)), never-early-exercised American puts ((2)), synthetic European puts ((3)), as well as spread portfolios long an optimally-early-exercised American and short its equivalent synthetic European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American and short its equivalent synthetic European put ((2)–(3)). The table further reports the moneyness (column (4)) and days-to-maturity ((5)) of the put pairs. The descriptive statistics include the mean, the standard deviation (StDev), the mean's t-statistic (Mean/StError), the bootstrapped 95% confidence interval for that t-statistic (95%BS-CI), several percentiles, and the number of observations. We match the observations in columns (1), (2), and (3), so that each observation in one column corresponds to exactly one observation in another. We calculate moneyness as the ratio of strike price to stock price. With the exception of the t-statistic and the 95% confidence interval, we calculate each statistic as the time-series mean taken over the cross-sectional statistic.

	Monthly Put Return (%)			Monthly Spread Return (%)			Fundamentals	
	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE	Initial Money-ness	Initial Maturity Time
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)	(4)	(5)
Panel A: Raw Returns								
Mean	−7.69	−10.96	−10.07	2.38	3.27	−0.89	1.00	73
StDev	70.82	68.99	76.08	31.64	27.02	14.20	0.08	26
Mean/StError	[−3.33]	[−4.99]	[−4.21]	[5.58]	[8.71]	[−3.75]		
95%BS-CI	{−2.12;1.84}	{−2.13;1.85}	{−2.13;1.85}	{−1.93;1.97}	{−2.09;1.81}	{−1.77;2.29}		
Percentile 1	−94.12	−94.16	−97.79	−88.24	−61.75	−49.38	0.82	45
Percentile 5	−86.13	−86.31	−91.01	−31.13	−14.80	−17.47	0.86	45
Quartile 1	−56.76	−58.01	−61.53	−3.87	−0.22	−2.87	0.95	48
Median	−22.46	−25.10	−25.76	0.88	0.00	0.36	1.00	69
Quartile 3	23.68	17.76	20.47	6.81	1.90	3.33	1.05	98
Percentile 95	118.33	111.77	123.49	44.22	38.12	12.65	1.14	111
Percentile 99	233.14	229.58	256.04	106.06	105.60	26.61	1.18	111
Observations	2,098	2,098	2,098	2,098	2,098	2,098	2,098	2,098
Panel B: Delta-Hedged Returns								
Mean	−0.74	−0.45	−0.24	−0.50	−0.29	−0.22	1.00	73
StDev	4.33	4.43	4.51	1.70	0.84	1.52	0.08	26
Mean/StError	[−5.21]	[−2.85]	[−1.47]	[−12.20]	[−10.98]	[−9.36]		
95%BS-CI	{−2.06;1.88}	{−2.08;1.87}	{−2.09;1.87}	{−1.80; 2.16}	{−1.74;2.34}	{−2.00;1.94}		
Percentile 1	−11.01	−10.85	−10.35	−6.27	−3.86	−5.32	0.82	45
Percentile 5	−6.84	−6.66	−6.38	−3.19	−1.73	−2.46	0.86	45
Quartile 1	−2.92	−2.69	−2.53	−1.03	−0.16	−0.65	0.95	48
Median	−0.91	−0.65	−0.52	−0.27	−0.01	−0.09	1.00	69
Quartile 3	1.14	1.47	1.64	0.23	0.00	0.35	1.05	98
Percentile 95	5.77	6.25	6.66	1.50	0.01	1.66	1.14	111
Percentile 99	12.27	12.99	13.80	3.44	0.21	3.61	1.18	111
Observations	2,098	2,098	2,098	2,098	2,098	2,098	2,098	2,098

Table 5: Put Portfolios Sorted on Moneyness and Days-to-Maturity

The table presents the mean monthly raw returns of moneyness and days-to-maturity sorted optimally-early-exercised American (column (1)), never-early-exercised American ((2)), and synthetic European ((3)) put portfolios as well as spread portfolios long an optimally-early-exercised American and short its equivalent synthetic European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American put and short its equivalent synthetic European put ((2)–(3)). At the end of sample month $t-1$, we first sort the puts into portfolios according to whether their strike-to-stock price ratio ("moneyness") lies above 1.05 (Panel A), between 0.95 and 1.05 (Panel B), or below 0.95 (Panel C). Within each moneyness portfolio, we next sort them into portfolios according to whether their days-to-maturity are below 60, between 60 and 90, or above 90 days. We equally-weight the portfolios and hold them over month t. We match the observations in columns (1), (2), and (3), so that each observation in one column corresponds to exactly one observation in another column. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Monthly Put Return (%)			Monthly Spread Return (%)		
Days-to-Maturity	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)
Panel A: In-The-Money Puts (Strike/Stock > 1.05)						
30-60	−12.10***	−18.78***	−18.39***	6.29***	6.59***	−0.39***
	[−7.19]	[−9.21]	[−8.66]	[6.65]	[7.44]	[−3.21]
60-90	−7.63***	−10.25***	−9.89***	2.26***	2.56***	−0.36***
	[−5.47]	[−7.04]	[−6.58]	[4.16]	[5.04]	[−3.90]
90-120	−5.29***	−6.78***	−6.45***	1.16***	1.45***	−0.32***
	[−4.26]	[−5.38]	[−4.94]	[3.04]	[4.00]	[−4.40]
Panel B: At-The-Money Puts (Strike/Stock 0.95-1.05)						
30-60	−11.45***	−16.45***	−15.92***	4.47***	5.00***	−0.53**
	[−4.27]	[−6.45]	[−5.81]	[6.26]	[7.29]	[−2.21]
60-90	−7.24***	−9.16***	−8.46***	1.22***	1.92***	−0.70***
	[−3.40]	[−4.70]	[−4.08]	[4.03]	[6.19]	[−3.96]
90-120	−4.58**	−5.53***	−4.79**	0.21	0.95***	−0.74***
	[−2.63]	[−3.30]	[−2.66]	[1.12]	[5.50]	[−4.67]
Panel C: Out-Of-The-Money Puts (Strike/Stock < 0.95)						
30-60	−6.83	−10.86***	−8.39*	1.57*	4.03***	−2.46***
	[−1.74]	[−2.99]	[−2.03]	[1.88]	[6.04]	[−3.88]
60-90	−6.78**	−7.95**	−6.46*	−0.32	1.18***	−1.49***
	[−2.30]	[−2.83]	[−2.04]	[−0.85]	[4.64]	[−3.25]
90-120	−3.78	−4.12*	−2.80	−0.98***	0.35***	−1.32***
	[−1.55]	[−1.73]	[−1.05]	[−3.12]	[2.30]	[−3.67]

Table 6: Put Portfolios Univariately Sorted on Stock Volatility

The table gives the mean monthly raw returns of univariate stock-volatility-sorted American and synthetic European put portfolios as well as of spread portfolios long one of the American and short the corresponding European put portfolio controlling for moneyness. While Panel A allows for optimal early exercises of the American puts over the return period, Panel B does not do so. At the end of each sample month $t-1$, we first sort puts into portfolios according to the quintile breakpoints of Fama-French (1993)-Carhart (1997) idiosyncratic stock volatility estimated over the prior twelve months of daily data. At the end of the same month, we next independently sort them into portfolios according to the quintile breakpoints of the strike-to-stock price ratio ("moneyness"). We use the intersection of the two univariate portfolio sets to create equally-weighted double-sorted portfolios. We finally create stock-volatility portfolios controlling for moneyness by forming portfolios of portfolios taking equal positions in each double-sorted portfolio within one stock-volatility classification. We also form a spread portfolio long the top and short the bottom stock-volatility quintile ("High–Low"). We hold the portfolios over month t. We match the American and European put observations, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Idiosyncratic Stock Volatility Quintile					
	1(Low)	2	3	4	5(High)	High–Low
	(1)	(2)	(3)	(4)	(5)	(5)–(1)
Panel A: Optimally-Early-Exercised American Puts						
American Put	−10.26***	−8.67***	−7.47***	−5.68**	−5.99***	4.27**
	[−3.69]	[−3.46]	[−2.99]	[−2.43]	[−2.85]	[2.28]
European Put	−14.65***	−12.60***	−10.00***	−7.08***	−5.64**	9.01***
	[−5.02]	[−4.94]	[−3.74]	[−2.85]	[−2.51]	[4.16]
Spread	4.39***	3.93***	2.53***	1.40**	−0.35	−4.74***
	[7.37]	[8.13]	[5.71]	[2.69]	[−0.66]	[−9.01]
Panel B: Never-Early-Exercised American Puts						
American Put	−14.99***	−12.71***	−10.54***	−8.25***	−7.84***	7.15***
	[−5.68]	[−5.41]	[−4.29]	[−3.62]	[−3.76]	[3.58]
European Put	−14.65***	−12.60***	−10.00***	−7.08***	−5.64**	9.01***
	[−5.02]	[−4.94]	[−3.74]	[−2.85]	[−2.51]	[4.16]
Spread	−0.34	−0.11	−0.54**	−1.17***	−2.20***	−1.86***
	[−1.05]	[−0.44]	[−2.20]	[−4.51]	[−6.20]	[−4.74]
Mean Moneyness	0.999	0.999	0.999	1.000	1.000	

Table 7: Fama-MacBeth (1973) Regressions of Spread Return on Moneyness, Days-to-Maturity, and Idiosyncratic Stock Volatility

The table presents the results of Fama-MacBeth (1973) regressions of the raw return of a spread portfolio long an American and short its equivalent synthetic European put over month t on subsets of stock and put characteristics measured at the start of that month. While Panel A allows for optimal early exercises of the American puts over the return period, Panel B does not do so. The characteristics include the strike-to-stock price ratio ("moneyness"), time-to-maturity (as fraction of a year), and idiosyncratic stock volatility. We compute idiosyncratic stock volatility using the Fama-French (1993)-Carhart (1997) model estimated over the prior twelve months of daily data. We match the American and European put observations, so that each American put corresponds to exactly one European put. The plain numbers are monthly premium estimates (in decimals), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	(1)	(2)	(3)	(4)
Panel A: Optimally-Early-Exercised American Puts				
Constant	0.02***	−0.08***	0.06***	−0.06***
	[5.03]	[−3.32]	[9.02]	[−2.33]
Moneyness		0.16***		0.16***
		[6.04]		[6.17]
Time-to-Maturity		−0.26***		−0.25***
		[−7.54]		[−7.57]
Idiosyncratic Volatility			−0.08***	−0.08***
			[−8.89]	[−8.58]
Panel B: Never-Early-Exercised American Puts				
Constant	−0.01***	−0.08***	0.00	−0.07***
	[−4.24]	[−3.63]	[0.88]	[−3.18]
Moneyness		0.07***		0.07***
		[3.77]		[3.91]
Time-to-Maturity		0.01		0.01
		[1.09]		[1.22]
Idiosyncratic Volatility			−0.03***	−0.03***
			[−5.17]	[−5.34]

Table 8: Delta-Hedged Put Portfolios Sorted on Moneyness and Days-to-Maturity

The table presents the mean monthly delta-hedged returns of moneyness and days-to-maturity sorted optimally-early-exercised American (column (1)), never-early-exercised American ((2)), and synthetic European ((3)) put portfolios as well as spread portfolios long an optimally-early-exercised American and short its equivalent synthetic European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American put and short its equivalent synthetic European put ((2)–(3)). At the end of sample month $t-1$, we first sort the puts into portfolios according to whether their strike-to-stock price ratio ("moneyness") lies above 1.05 (Panel A), between 0.95 and 1.05 (Panel B), or below 0.95 (Panel C). Within each moneyness portfolio, we next sort them into portfolios according to whether their days-to-maturity are below 60, between 60 and 90, or above 90 days. We equally-weight the portfolios and hold them over month t. We match the observations in columns (1), (2), and (3), so that each observation in one column corresponds to exactly one observation in another column. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Monthly Put Return (%)			Monthly Spread Return (%)		
Days-to-Maturity	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)
Panel A: In-The-Money Puts (Strike/Stock > 1.05)						
30-60	−1.30***	−0.73***	−0.56***	−0.74***	−0.57***	−0.17***
	[−12.73]	[−6.02]	[−4.62]	[−15.21]	[−14.70]	[−7.23]
60-90	−0.86***	−0.38***	−0.25**	−0.61***	−0.48***	−0.13***
	[−8.66]	[−3.18]	[−2.17]	[−14.64]	[−14.24]	[−5.39]
90-120	−0.66***	−0.27**	−0.18	−0.48***	−0.39***	−0.09***
	[−6.14]	[−2.23]	[−1.55]	[−13.73]	[−13.36]	[−4.98]
Panel B: At-The-Money Puts (Strike/Stock 0.95-1.05)						
30-60	−0.89***	−0.56***	−0.39**	−0.50***	−0.32***	−0.18***
	[−7.62]	[−4.10]	[−2.75]	[−12.38]	[−11.08]	[−9.02]
60-90	−0.47***	−0.26*	−0.10	−0.36***	−0.21***	−0.16***
	[−3.70]	[−1.80]	[−0.72]	[−11.32]	[−8.54]	[−7.65]
90-120	−0.34**	−0.19	−0.04	−0.30***	−0.15***	−0.15***
	[−2.55]	[−1.28]	[−0.29]	[−10.94]	[−7.49]	[−8.92]
Panel C: Out-Of-The-Money Puts (Strike/Stock < 0.95)						
30-60	−1.18***	−0.97***	−0.48	−0.70***	−0.21***	−0.49***
	[−4.91]	[−3.73]	[−1.74]	[−9.62]	[−8.15]	[−8.66]
60-90	−0.52**	−0.41	−0.07	−0.44***	−0.10***	−0.34***
	[−2.21]	[−1.68]	[−0.29]	[−9.67]	[−6.05]	[−8.84]
90-120	−0.30	−0.23	0.04	−0.34***	−0.06***	−0.28***
	[−1.39]	[−1.05]	[0.18]	[−9.17]	[−5.35]	[−9.09]

Table 9: Delta-Hedged Put Portfolios Univariately Sorted on Stock Volatility

The table gives the mean monthly delta-hedged returns of univariate stock-volatility-sorted American and synthetic European put portfolios as well as of spread portfolios long one of the American and short the corresponding European put portfolio controlling for moneyness. While Panel A allows for optimal early exercises of the American puts over the return period, Panel B does not do so. At the end of each sample month $t-1$, we first sort puts into portfolios according to the quintile breakpoints of Fama-French (1993)-Carhart (1997) idiosyncratic stock volatility estimated over the prior twelve months of daily data. At the end of the same month, we next independently sort them into portfolios according to the quintile breakpoints of the strike-to-stock price ratio ("moneyness"). We use the intersection of the two univariate portfolio sets to create equally-weighted double-sorted portfolios. We finally create stock-volatility portfolios controlling for moneyness by forming portfolios of portfolios taking equal positions in each double-sorted portfolio within one stock-volatility classification. We also form a spread portfolio long the top and short the bottom stock-volatility quintile ("High–Low"). We hold the portfolios over month t. We match the American and European put observations, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Idiosyncratic Stock Volatility Quintile					
	1(Low)	2	3	4	5(High)	High–Low
	(1)	(2)	(3)	(4)	(5)	(5)–(1)
Panel A: Optimally-Early-Exercised American Puts						
American Put	−0.66***	−0.56***	−0.57***	−0.70***	−1.23***	−0.57***
	[−5.39]	[−4.36]	[−3.87]	[−4.51]	[−5.58]	[−3.14]
European Put	−0.30**	−0.20	−0.13	−0.15	−0.43*	−0.13
	[−2.13]	[−1.36]	[−0.75]	[−0.84]	[−1.91]	[−0.79]
Spread	−0.37***	−0.36***	−0.43***	−0.55***	−0.80***	−0.44***
	[−9.29]	[−10.41]	[−10.95]	[−11.40]	[−11.83]	[−8.70]
Panel B: Never-Early-Exercised American Puts						
American Put	−0.45***	−0.31**	−0.28	−0.38	−0.87***	−0.42**
	[−3.29]	[−2.15]	[−1.65]	[−0.38]	[−3.62]	[−2.17]
European Put	−0.30**	−0.20	−0.13	−0.15	−0.43*	−0.13
	[−2.13]	[−1.36]	[−0.75]	[−0.84]	[−1.91]	[−0.79]
Spread	−0.15***	−0.11***	−0.15***	−0.23***	−0.44***	−0.28***
	[−7.56]	[−6.26]	[−7.95]	[−8.13]	[−7.58]	[−5.67]
Mean Moneyness	0.999	0.999	0.999	1.000	1.000	

Table 10: Cross-Sectional Option Return Anomaly Variables

The table presents details on the 15 cross-sectional option return anomaly variables used in our replication exercise. While column (1) gives the names of the anomaly variables, column (2) identifies the studies in which they were originally proposed. Column (3) shows the journal in which those original studies are published (JF=Journal of Finance; JFE=Journal of Financial Economics; RFS=Review of Financial Studies; JFQA=Journal of Financial and Quantitative Analysis; RAPS=Review of Asset Pricing Studies; JFM=Journal of Financial Markets; QJF=Quarterly Journal of Finance; and WP=Working Paper). Column (4) reveals the type of option return analyzed in the original studies, whereas column (5) identifies the sample period used in their empirical work. Finally, column (6) describes the construction of the anomaly variables, with it also showing the pages in the original studies on which the construction of those variables is outlined in greater detail (in parentheses).

#	Anomaly	Authors/Publication Year	Journal	Return Type	Original Sample Period	Variable Definition
	(1)	(2)	(3)	(4)	(5)	(6)
1	Option Skewness	Boyer & Vorkink (2014)	JF	Raw put	1996-2009	Forward-looking Black-Scholes (1973) option return skewness (pp. 1490-1491);
2	Stock Volatility	Hu & Jacobs (2020)	JFQA	Raw put	1996-2013	Realized daily stock return volatility over the last twelve months (pp. 1033-1034);[1]
3	Realized-to-Implied Volatility	Goyal & Saretto (2009)	JFE	Straddle	1996-2006	Ratio of realized daily stock return volatility over the last twelve months to average of the one-month ATM call and put implied volatilities (pp. 312-313);
4	Implied Volatility Slope	Vasquez (2017)	JFQA	Straddle	1996-2012	Average of longer-than-50-days-to-maturity ATM call and put implied volatilities minus average of the one-month ATM call and put implied volatilities (p. 2731);
5	Idiosyncratic Stock Volatility	Cao & Han (2013)	JFE	Δ-hedged put	1996-2009	Fama-French (1993) idiosyncratic stock return volatility estimated over the last month of daily data (p. 234);
6	Volatility-of-Volatility	Ruan (2020); Cao et al. (2023)	JFM; QJF	Δ-hedged put	1996-2016	Volatility of daily average of the one-month ATM call and put implied volatilities over the last month (pp. 5-8; p. 12);
7	Moneyness	Frazzini & Pedersen (2022)	RAPS	Δ-hedged put	1996-2018	Absolute Black-Scholes (1973) put delta (p. 9);
8	Embedded Leverage	Frazzini & Pedersen (2022)	RAPS	Δ-hedged put	1996-2018	Absolute Black-Scholes (1973) put delta times underlying stock-to-option price ratio (p. 2);
9	Lending Fee	Ramachandran & Tayal (2021)	JFE	Δ-hedged put	2006-2017	Ratio of loaned underlying stock shares to total loanable supply of those shares (p. 301);
10	Cash Flow Volatility	Zhan et al. (2022)	RFS	Δ-hedged put	1996-2016	Volatility of cash flow-to-market capitalization of underlying stock over the prior five years (pp. 1401-1403);
11	Cash and Equivalents	Zhan et al. (2022)	RFS	Δ-hedged put	1996-2016	Ratio of a firm's cash holdings to its total assets p. 1403);
12	Analyst Disagreement	Zhan et al. (2022)	RFS	Δ-hedged put	1996-2016	Ratio of a firm's annual EPS forecast volatility to its absolute mean outstanding forecast (p. 1403);
13	Share Issuances	Zhan et al. (2022)	RFS	Δ-hedged put	1996-2016	Split-adjusted share issuances over the last twelve months (p. 1403);
14	Profitability	Zhan et al. (2022)	RFS	Δ-hedged put	1996-2016	Ratio of a firm's net profits before extraordinary items to its book equity value (p. 1403);
15	Stock Price	Boulatov et al. (2022)	WP	Δ-hedged put	1996-2020	Underlying stock price (p. 14);

We focus on Hu and Jacobs's (2020) twelve-month stock return volatility since it yields their strongest put return results (see their Table 5).

Table 11: Replication Exercise

The table presents the mean monthly returns of anomaly spread portfolios either not allowing (column (1)) or allowing ((2)) for optimal early exercises of the underlying American puts, the signed difference across the never-early-exercise and the optimal-early-exercise case ((2)–(1)), and the absolute percent difference across them ((3)). We form the spread portfolios as follows. At the end of sample month $t-1$, we first sort the appropriate test assets into portfolios according to the quintile breakpoints of an anomaly variable. We equally-weight the portfolios and hold them over month t. We finally form a spread portfolio by longing the top anomaly variable portfolio and shorting the bottom portfolio. The test assets in Panels A, B, and C are single-stock American puts, single-stock straddles (i.e., spread portfolios long a single-stock American call and long its equivalent single-stock American put), and delta-hedged single-stock American puts. See Table 10 for more details about the anomaly variables including their definition. The absolute percent difference is the absolute value of column (2)–(1) scaled by the absolute value of column (1). Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Never Early Exercised	Optimally Early Exercised	Signed Diff.	Absolute Percent Diff.
	(1)	(2)	(2)–(1)	(3)
Panel A: Raw Put Studies				
Option Skewness	−10.66***	−5.57*	5.09***	47.7%
	[−4.24]	[−2.06]	[6.98]	
Stock Volatility	9.30***	5.06*	−4.25***	45.6%
	[3.53]	[2.03]	[−5.81]	
Panel B: Straddle Studies				
Realized-to-Implied Volatility	4.40***	5.24***	0.84**	19.2%
	[4.73]	[5.59]	[2.57]	
Implied Volatility Slope	2.88***	4.01***	1.13***	39.3%
	[4.43]	[6.67]	[3.85]	
Panel C: Delta-Hedged Put Studies				
Idiosyncratic Stock Volatility	−0.58***	−0.83***	−0.25***	42.6%
	[−3.06]	[−4.80]	[−6.47]	
Volatility-of-Volatility	−0.82***	−1.01***	−0.19***	23.1%
	[−6.06]	[−7.69]	[−7.06]	
Moneyness	2.09**	1.34*	−0.76***	36.1%
	[2.72]	[1.77]	[−5.39]	
Embedded Leverage	−2.64**	−2.03*	0.61***	23.1%
	[−2.21]	[−1.80]	[3.51]	
Lending Fee	−0.71***	−0.80***	−0.08***	11.5%
	[−7.83]	[−8.27]	[−3.85]	
Cash Flow Volatility	−0.46***	−0.61***	−0.15***	31.8%
	[−4.26]	[−5.82]	[−6.57]	
Cash and Equivalents	−0.38**	−0.44***	−0.05*	13.5%
	[−2.43]	[−3.10]	[−1.83]	
Analyst Disagreement	−0.49***	−0.61***	−0.13***	25.9%
	[−5.02]	[−7.13]	[−5.60]	
Share Issuances	0.21*	0.13	−0.09***	40.5%
	[1.60]	[1.07]	[−3.29]	
Profitability	0.40***	0.51***	0.11***	26.6%
	[3.26]	[4.68]	[3.26]	
Price	0.48***	0.74***	0.26***	53.4%
	[4.11]	[6.34]	[8.17]	

Internet Appendix:
The Early Exercise Risk Premium

AUTHOR 1 and AUTHOR 2

In this Internet Appendix, we offer supplementary simulation and empirical evidence on the early exercise risk premium in plain-vanilla puts. Section IA.1 starts with reviewing the theoretical literature on the Longstaff and Schwartz (2001) method, also showing that our early exercise risk premium estimates obtained from that method converge. In Section IA.2, we show how the additional SV and SVJ parameters affect the early exercise risk premium (Tables IA.1 and IA.2). Section IA.3 looks into that same premium obtained from SV and SVJ processes calibrated to stock market indexes (Tables IA.3 and IA.4). In Section IA.4, we run a simulation exercise to assess the effect of the optimal early exercise rule approximation used in our empirical work on our main conclusions (Table IA.5). In Section IA.5, we repeat our main cross-sectional tests using *almost-held-to-maturity* put returns for the shortest and corresponding returns for longer time-to-maturity puts (Tables IA.6 and IA.7). Section IA.6 presents the mean returns of option-price (rather than equally) weighted moneyness, time-to-maturity, and stock volatility portfolios (Tables IA.8 and IA.9). Section IA.7 offers subperiod evidence to study the effect of the interest rate on the early exercise risk premium (Table IA.10). In Section IA.8, we validate that our main cross-sectional conclusions are not attributable to short-sale constrained stocks (Table IA.11); those stocks or illiquid American calls, American puts, and/or stocks (Table IA.12); and the identification of zero-dividend stocks (Table IA.13). Section IA.9 finally shows that real investors can earn the early exercise risk premium, at least in case of high optimal-early-exercise-probability puts under realistic stock and option transaction costs (Table IA.14).

IA.1 Convergence of the Early Exercise Risk Premium Estimates Computed Using the Longstaff-Schwartz (2001) Method

In our Monte Carlo simulation exercise in Section 2.2 of our main paper, we crucially rely on the ability of the Longstaff-Schwartz (2001) American option valuation method to yield precise estimates of optimal early exercise thresholds and American put values to compute meaningful early exercise risk premiums. Given that, it is worth noting that a large literature in mathematical finance studies the theoretical and empirical properties of that method. To briefly summarize the most relevant studies from that literature, Clement et al. (2002) and Stentoft (2004) offer mathematical proofs that the Longstaff-Schwartz (2001) value estimate converges to the true option value with the number of sample paths both in a GBM but also in more general worlds with stochastic volatility and/or jumps. In accordance, Wang and Caflisch (2009) and Tompaidis and Yang (2014) establish that the estimate comes extremely close to the true value in Merton's (1976) mixed jump-diffusion world under no more than 250,000 sample paths. Conversely, Fabozzi et al. (2014) establish that the estimate does the same in the SVJ world under a comparable number of sample paths. Given that we use five million (rather than 250,000) sample paths in our simulation exercise, it is thus likely that our early exercise risk premium estimates must also be close to their true values.

We next offer some more direct evidence that our early exercise risk premium estimates obtained from the Longstaff-Schwartz (2001) method indeed converge over five million sample paths in the SV and SVJ worlds.[1] To achieve that goal, Figure IA.1 plots the SV (Panel A) and SVJ (Panel B) estimates obtained from the 27 parameter value sets in Table 2 in our main paper against the number of sample paths used in our simulations, letting that number range from 100,000 to five million in

[1]We directly focus on the SV and SVJ worlds since the estimates in the GBM world converge far more rapidly, owing to the fact that there is only one state variable in the GBM world but two in the SV and SVJ worlds.

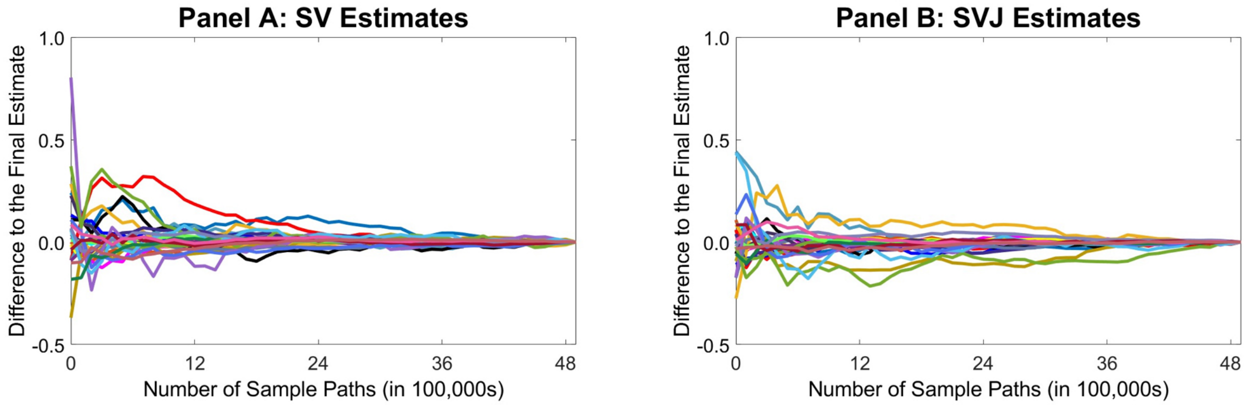

Figure IA.1: Convergence of the Longstaff-Schwartz (2001) Early Exercise Risk Premium Estimates in the SV and SVJ Worlds The figure plots the Longstaff-Schwartz (2001) early exercise risk premium estimates under the stochastic volatility (SV; Panel A) and stochastic volatility-jump (SVJ; Panel B) processes for each of the 27 parameter value sets used in Table 2 in our main paper against the number of sample paths used in the simulation. We describe the 27 parameter value sets used in Table 2 in our main paper in Section 2.2.1 of that paper. We let the number of sample paths increase from 100,000 to five million in increments of 100,000.

increments of 100,000. To improve readability, the figure shows each estimate for some parameter value set net of its final estimate, so that all lines eventually end up at zero. The figure suggests that the SV and SVJ premium estimates rapidly approach some constant value with the number of sample paths. To be more specific, the standard deviation over the final five SV estimates (i.e., those obtained from 4.6 to 5.0 million sample paths) per parameter value set is, on average, only about 0.003%, with only those for the short days-to-maturity out-of-the-money (OTM) puts on the low (0.010%) and intermediate (0.010%) volatility asset markedly above that. Conversely, the standard deviation over the final five SVJ estimates per parameter value set is also, on average, only about 0.003%, with no single estimate above 0.008%. Given that the early exercise risk premium estimates in Table 2 in our main paper are in percent, the standard deviation around those estimates is small. Using the 1.400% SV estimate for the 30 days-to-maturity in-the-money (ITM) put on the high volatility asset as example (see the third row in Panel B of Table 2 in our main paper), the estimate minus (plus) two times the standard deviation over the final five estimates is 1.394% (1.406%).[2]

[2]In unreported tests, we also verify that our simulation evidence is robust to choosing a higher-order polynomial as regression function to model the alive put value. Our results from those tests align with the widely-held sentiment that

Overall, the studies cited above and our evidence in Figure IA.1 imply that the early exercise risk premium estimates in our main paper are likely to be reasonably precise.

IA.2 The Effects of the Additional SV and SVJ Stochastic Process Parameters on the Early Exercise Risk Premium

We now shed more light on how the additional stochastic process parameters in the SV and SVJ worlds affect the early exercise risk premium estimates obtained from the Longstaff-Schwartz (2001) method in Section 2.2 of our main paper. To that end, Table IA.1 (IA.2) in this Internet Appendix reports those estimates under the basecase parameter values outlined in Section 2.2.1 of our main paper plus a high (upper subpanel) or low (lower subpanel) value for each of the additional SV (SVJ) parameters. The additional SV parameters are the volatility of variance (σ_v; Panel A), the physical mean reversion in variance speed ($\kappa^{\mathbb{P}}$; Panel B), the asset value-variance correlation (ρ; Panel C), and the variance risk premium parameter (γ; Panel D). Conversely, the additional SVJ parameters are the physical jump intensity ($\lambda^{\mathbb{P}}$; Panel A), the physical mean jump size ($\mu_z^{\mathbb{P}}$; Panel B), and the jump intensity (Panel C) and size (Panel D) risk. While columns (1) to (3), (4) to (6), and (7) to (9) in each table look into ITM (strike-to-stock price = 1.05), at-the-money (ATM; 1.00), and OTM (0.95) puts, respectively, columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9) consider puts with 30, 60, and 90 days-to-maturity, respectively. In turn, the first three rows in each subpanel focus on puts on an asset with a 15%, 30%, and 45% annualized volatility, respectively.

Since our aim is to explore the effects of substantiative but realistic variations in the additional parameters, we again rely on the estimation output of Pollastri et al. (2023) who calibrate the SV and SVJ stochastic processes to the single stocks in the S&P 500 index. In this case, we however

the Longstaff-Schwartz (2001) method is insensitive to the choice of the regression function. In private correspondence, Professor Francis Longstaff, for example, writes us: "Back when we did the paper, we found that the choice of the basis function really had little effect on the results. Since almost anything seemed to work pretty well, we used simple polynomials. There was a subsequent literature among operations research and math types where they used various alternatives such as orthogonal polynomials, sines and cosines, etc. [...]. I think they all came to the conclusion that it did not matter what types of basis functions you used—any reasonable choice worked pretty well."

choose as low value for each parameter the 2.5th percentile of its single-stock estimates and as high value the 97.5th percentile reported in their Tables 1 and 2. As a result, we set σ_v to 20% or 60% per annum, $\kappa^{\mathbb{P}}$ to two or ten, ρ to –0.10 or –0.50, and γ to zero (the stochastic volatility without variance risk premium case) or minus twelve. Conversely, we set $\lambda^{\mathbb{P}}$ to 0.50 or 6.00, $\mu_z^{\mathbb{P}}$ to –0.02 or 0.05, jump intensity risk to $\lambda^{\mathbb{Q}} = \lambda^{\mathbb{P}}$ or $2\lambda^{\mathbb{P}}$, and jump size risk to $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}} - 0.08$ or $\mu_z^{\mathbb{P}}$.

Table IA.1 suggests that the effects of the additional SV parameters again come through the direct and indirect effects of stochastic volatility on the optimal early exercise probability. As we discuss in Section 2.2 in our main paper, the direct effect arises through a stronger stochastic volatility affecting the trajectory of the underlying asset's value over the time-to-maturity, inducing the put owner to either speed up or delay optimal early exercises. Recall, for example, that a stronger stochastic volatility implies that an ITM (OTM) American put on a low-current-volatility asset can still move OTM (ITM) over its time-to-maturity, inducing the owner to speed up (delay) optimally early exercising. Conversely, the indirect effect arises through the ability of puts to hedge against high-volatility states when stochastic volatility is more negatively priced (i.e., the variance risk premium is more negative), always inducing the put owner to delay optimal early exercises.

TABLE IA.1 ABOUT HERE

In accordance, the table reveals that since a higher volatility of variance, a lower (i.e., less positive) mean reversion speed, and a lower (i.e., more negative) asset value-volatility correlation amplify the direct effect, they induce the early exercise risk premiums of ITM puts on low-current-volatility assets to rise but those of all other puts to fall (see Panels A to C). While an increase in the volatility of variance from 20% per annum to 60%, for example, induces the premium of 30-day ITM puts on a 15% annual volatility asset to rise from 7.08% per month to 7.47%, that same increase induces the premium of the 30-day ATM puts on that same asset to drop from 3.45% to 2.65% (compare subpanels A.1 and A.2). Similarly, while a decrease in the mean reversion speed from ten to two induces the premium of 60-day ITM puts on a 15% annual volatility asset to rise from 2.82% to 3.10%, that same decrease induces the premium of the 60-day ATM puts on that same asset to drop from 0.56% to

0.42% (compare subpanels B.1 and B.2). Noteworthily, however, the table also clarifies that the direct effect is only positive when current volatility is low (i.e., 15% in the table). Specifically, when current volatility is 30% or 45%, a higher volatility of variance, a lower mean reversion speed, and a higher asset value-volatility correlation always induce the early exercise risk premium to fall since, in those cases, the benefits from volatility increases (coming through the put potentially moving deeper ITM) always outweigh their costs, inducing the put owner to delay early exercising.

Further supporting our argumentation, the table also indicates that a more negative variance risk premium amplifies the indirect effect, consistently lowering the early exercise risk premium (see Panel D). A decrease in the variance risk premium scaling factor, γ, from zero (no variance risk premium) to minus twelve, for example, lowers the premium of 60-day ITM puts on a 30% volatility asset from 0.52% per month to 0.37%. In line with the direct effect, the table also demonstrates that the indirect effect is the most pronounced for puts on low-current-volatility assets.

In contrast, Table IA.2 suggests that the effects of the additional SVJ parameters mostly come through the indirect effect of asset-value jumps on the optimal early exercise probability, simply because our simulations include small but frequent jumps and we offset the additional volatility generated through those by lowering long-run (and thus current) diffusive volatility (recall Section 2.2 in our main paper). The indirect effect of jumps arises since the jumps in our simulations occur predominately in high marginal-utility states and tend to be more downward in those states, rendering puts well suited to hedge against jump risk by offering a high payout upon a downward jump in such a state and inducing their owner to delay early exercising them. In line with that insight, Panels A and B of the table show that since a higher physical jump probability and a more negative mean jump size amplify the indirect effect, they induce the early exercise risk premium to fall. An increase in the physical jump intensity from 0.50 to 6.00, for example, induces the early exercise risk premium of 30-day ITM puts on a 30% annual volatility asset to drop from 2.39% per month to 1.83% (compare subpanels A.1 and A.2). More directly, since a higher jump intensity risk and a higher mean jump size risk also amplify the indirect effect, they also lead the premium to fall (see

Panels C and D). An increase in mean jump size risk from $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}}$ to $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}} - 0.08$, for example, leads the premium of 30-day ATM puts on a 30% annual volatility asset to drop from 1.59% per month to 1.16% (compare subpanels D.1 and D.2).

TABLE IA.2 ABOUT HERE

Taken together, the simulation evidence in this section corroborates that variations in the SV and SVJ parameters condition the strengths of the direct and indirect effects of stochastic volatility and/or asset-value jumps on the optimal early exercise probability in line with our intuition, leading to the anticipated effects on the raw or delta-hedged early exercise risk premium.

IA.3 The Early Exercise Risk Premium in Stock Index Puts

We next look into the theoretical early exercise risk premium in stock *index* puts in the SV and SVJ worlds. Toward that end, we apply the Longstaff-Schwartz (2001) American option valuation method to SV and SVJ stochastic processes calibrated to the S&P 500 stock index (see Section 2.2.1 in our main paper for more details about our methodology). In our main paper, we instead apply that same method to SV and SVJ processes calibrated to single stocks since we later conduct empirical tests on single-stock puts. Notwithstanding, we believe that it is also interesting to investigate the theoretical early exercise risk premium in stock index puts, especially since far more studies estimate the additional SV and SVJ parameters for stock indexes than single stocks.

Table IA.3 shows the early exercise risk premium in stock index puts in the SV world under the SV parameter estimates extracted from S&P 500 stock index data by Bates (2000; Panel A), Eraker (2004; Panel B), Hurn et al. (2015; Panel C), and Jacobs and Liu (2019; Panel D). For simplicity, we state the SV parameter estimates in the panel headings.[3,4] While columns (1) to (3), (4) to (6), and

[3]As in our main paper, we assume that the initial stock index price, $S(0)$, is 50, the physical drift rate, $\alpha^{\mathbb{P}}$, is 12% per annum, and the risk-free rate of return, r_f, is 2.5% per annum.

[4]The table headings reveal that, in comparison to single stocks, the S&P 500 stock index yields a slower physical mean reversion in variance speed (i.e., its average $\kappa^{\mathbb{P}}$ estimate is only about 2.50 relative to 6.00 for single stocks) and a more negative asset value-variance correlation (i.e., its average correlation ρ estimate is about –0.70 relative to –0.25 for single stocks), but a similar volatility of variance (σ_v) and variance risk premium parameter (γ).

(7) to (9) consider ITM (strike-to-stock price: 1.05), ATM (1.00), and OTM (0.95) puts, columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9) focus on 30, 60, and 90 days-to-maturity puts. In contrast, the first, second, and third row in each panel dwells into puts written on an asset with an annualized volatility of 15%, 30%, and 45%, respectively. The table suggests that the raw early exercise risk premium in stock index puts is, if anything, more positive than the same premium in single stocks. To be specific, while the raw single-stock premium is generally positive and can reach up to 7.28% per month (see Table 2 in our main paper), the raw stock-index premium is also generally positive but can exceed 11% (see Panel D). Except for ITM puts on low volatility assets, the delta-hedged stock-index premium (not shown in table) is negative but an order of magnitude smaller than the raw premium, as in the single-stock case. Finally, moneyness, time-to-maturity, and volatility condition the raw and delta-hedged stock-index premiums just like they condition their single-stock counterparts (compare Table 2 in our main paper with Table IA.3).

TABLE IA.3 ABOUT HERE

Table IA.4 reports the early exercise risk premium in stock index puts in the SVJ world under the SVJ estimates extracted from S&P 500 stock index data by Eraker (2004; Panel A), Broadie et al. (2009; Panel B), Hurn et al. (2015; Panel C), and Jacobs and Liu (2019; Panel D).[5] Using a design identical to Table IA.3, the table reveals that the raw stock-index premium is generally positive but can vary greatly from the raw single-stock premium. To wit, while the raw single-stock premium can reach up to 4.03% per month (see Table 2 in our main paper), the raw stock-index premium is only close to that number under Eraker's (2004) and Broadie et al.'s (2009) estimates (4.54% and 5.68%; see Panels A and B) but much higher under Hurn et al.'s (2015) and Jacobs and Liu's (2019) estimates (11.14% and 8.92%; see Panels C and D), all respectively. In agreement, the delta-hedged stock-index premium (again not shown) is always negative under the former sets of estimates but only negative for all but ITM puts on low volatility assets for the latter sets. Noteworthily, the

[5]The table headings reveal that, in comparison to single stocks, the S&P 500 stock index jumps less often (i.e., its average physical jump intensity $\lambda^{\mathbb{P}}$ estimate is only slightly above one relative to 3.50 for single stocks) but with a similar physical mean jump size and volatility relative to the average single stock.

reason for this divergence is that asset-value jumps are systematically riskier under the former rather than latter sets. To be specific, while Hurn et al.'s (2015) and Jacobs and Liu's (2019) physical and risk-neutral jump intensity or mean jump size are either identical or close to one another, Eraker (2004) and Broadie et al. (2009) estimate a far larger wedge between the physical and risk-neutral values for those parameters. As a result, moneyness, time-to-maturity, and volatility only always condition the raw but not necessarily the delta-hedged stock-index premium just like they condition their single-stock counterparts (compare Table 2 in our main paper with Table IA.4).

Table IA.4 About Here

In sum, the simulation evidence in this section suggests that the early exercise risk premiums in single-stock and stock-index puts behave similarly in the SV world. In contrast, the two premiums can diverge in the SVJ world depending on the systematic risk of asset-value jumps.

IA.4 The Optimal Early Exercise Rule Approximation

In our empirical analysis, we assume that an optimal early exercise of an American put occurs as soon as the put's end-of-day price is sufficiently close to its end-of-day early exercise payoff or, equivalently, if the underlying-asset's price lies within a 5% distance of the optimal early exercise threshold (see Section 3.2 in our main paper). We have to rely on this assumption since the absence of arbitrage opportunities implies that the put's price can never drop below the early exercise payoff, whereas minimum tick size rules imply that it can also never be identical to that payoff. We next offer some theoretical evidence on the effect of this "optimal early exercise rule approximation" on our empirical conclusions. Toward that goal, we repeat the simulation exercise in Table 2 of our main paper, either assuming that an American put is early exercised as soon as its underlying-asset value crosses the optimal early exercise threshold from above (as in the original table) or, alternatively, as soon as it comes within a 5% distance to the optimal threshold.

Table IA.5 presents the results from that exercise, with Panels A, B, and C focusing on the GBM, SV, and SVJ worlds, respectively. While columns (1), (2), and (1)–(2) focus on ITM (strike-to-stock price = 1.05) puts, columns (3), (4), and (3)–(4) look into ATM (1.00) and columns (5), (6), and (5)–(6) OTM (0.95) puts. Conversely, the rows within each panel consider 30, 60, and 90 days-to-maturity puts written on 15%, 30%, and 45% annual volatility assets. Crucially, the columns titled "Appr." give the early exercise risk premium obtained from our optimal early exercise rule approximation, those titled "Exact" the premium obtained from the exact rule, and those titled "Diff." the difference between the two premiums. The table shows that the optimal early exercise rule approximation should, at least in theory, not greatly distort the early exercise risk premium estimates derived in our empirical work. In particular, the differences between the premiums obtained from the two rules are, in the vast majority of cases, no larger than a few basis points. Looking, for example, into 30-day ATM puts on 30% volatility assets in the SVJ world, the approximated premium is 1.45%, the exact premium is 1.43%, and the difference is a mere 0.02%. In line with intuition, the table further suggests that the difference is larger for shorter-maturity-time deeper-ITM puts written on lower volatility assets, with, however, even those puts producing a relatively small bias.

Table IA.5 About Here

Overall, this section suggests that the optimal early exercise rule approximation used in our empirical work should, at least in theory, not greatly distort our main empirical results.

IA.5 Closer-to-Maturity Put Returns

In our main empirical work, we use sold-before-maturity (and not held-to-maturity) calendar-month returns even for the shortest time-to-maturity options to address the well-known problem that option prices become increasingly inaccurate close to their maturity dates. We can see the severity of that problem from Figure IA.2, showing that about 98%, 24%, and 12% of our sample option prices violate basic arbitrage bounds one, ten, and 20 days before maturity, respectively. While the inaccurate option prices do not stop other cross-sectional raw option return studies from calculating held-to-maturity

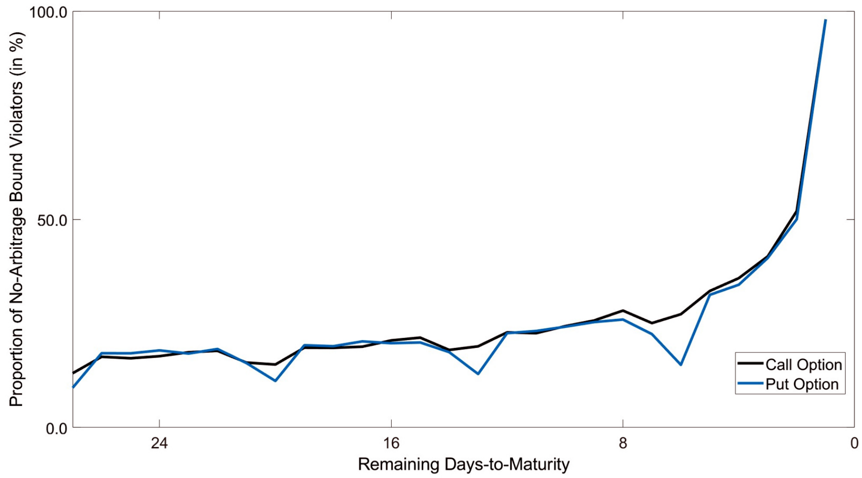

Figure IA.2: Proportions of No-Arbitrage-Bound Violators Over the Final Days-to-Maturity The figure plots the proportions of sample calls (black line) and puts (blue line) which violate standard no-arbitrage bounds used in cross-sectional option return studies over those options' final 28 days-to-maturity.

returns since they use the stock (and not option) price to measure the option's payoff, they stop us from doing so because we require accurate option prices until maturity to meaningfully compare the early exercise payoff and the option price at the end of each trading day to identify optimal early exercises over the return horizon. Noteworthily, the inaccurate prices also stop cross-sectional delta-hedged option return studies from calculating held-to-maturity returns because these studies require accurate option deltas until maturity to calculate the replication portfolio's payoff.[6,7]

Notwithstanding, we next study whether our main empirical conclusions change if we rely on raw option returns closer to held-to-maturity returns for the shortest time-to-maturity options. In doing so, we look into *almost-held-to-maturity* returns for those options, calculated over the four-calendar-

[6]While the delta-hedged option return studies of Goyal and Saretto (2009) and Boulatov et al. (2022) seem to be exceptions to that rule, they do not rebalance the replication portfolios in their delta-hedged positions, implying that they only require option deltas at the start of their return periods. In contrast to them, all other studies in that literature rebalance their replication portfolios at a daily frequency, implying that they require daily deltas over their return horizons and thus also investigate sold-before-maturity (and not held-to-maturity) returns.

[7]In private correspondence, Professor Stephen Figlewski told us that the high proportions of no-arbitrage bound violations close to maturity probably arise for the following reasons. First, market-makers have little incentives to post competitive bid and ask quotes since, first, they can only earn small profits from selling near-maturity options while still incurring high costs from delta-hedging those (especially in the presence of jumps) and, second, liquidity is extremely low for near-maturity options unless they are right ATM. In addition, option price indivisibilities can induce the option midpoint price to greatly deviate from its true value for small-price options with a low time value.

week period ending at the start of the option expiration week. We refrain from directly looking into held-to-maturity returns since Figure IA.2 suggests that our sample option prices are simply too inaccurate over the last five trading days to meaningfully identify optimal early exercises. Conversely, we calculate the intermediate (longest) time-to-maturity option returns over the four-calendar-week period ending at the start of the return period for the shortest (intermediate) time-to-maturity options. Except for the changes in the return periods, we then calculate optimally-early-exercised American put returns, never-early-exercised American put returns, and synthetic European put returns as described in Section 3.2 of our main paper ("closer-to-maturity sample").

Using the same designs as the corresponding tables in our main paper, Table IA.6 shows descriptive statistics for the closer-to-maturity sample, whereas Table IA.7 presents the results from repeating the FM regressions in Table 7 of our main paper on that sample. Table IA.6 demonstrates that the pooled-sample mean spread return across optimally-early-exercised American and their equivalent synthetic European puts (i.e., the raw single-stock-put early exercise risk premium) remains positive and highly significant (t-statistic: 2.74) in the closer-to-maturity sample (see column (1)–(3)). Also, the same return across never-early-exercised American and their equivalent synthetic European puts continues to be negative and highly significant (t-statistic: –4.01) in that sample (see column (2)–(3)). Turning to the FM regressions, Panel A of Table IA.7 suggests that the spread return across equivalent American and European puts still significantly increases with moneyness (t-statistic: 6.12) but decreases with days-to-maturity (t-statistic: –5.75) and stock volatility (t-statistic: –2.99) upon us allowing for optimal early exercises in the closer-to-maturity sample (see column (4)). In contrast, Panel B shows that not allowing for such exercises in that sample again weakens the effect of moneyness and stock volatility on that spread return, while it renders the effect of time-to-maturity insignificant (same column).

Tables IA.6 and IA.7 About Here

While the evidence obtained from the closer-to-maturity sample is good news insofar as it aligns with that from the sample used in our main paper, it nonetheless also points to the dangers from using inaccurate option prices in our empirical work. To see that, note that the pooled-sample mean monthly spread return across optimally-early-exercised American and their equivalent synthetic European puts calculated from the closer-to-maturity sample, 1.51% (t-statistic: 2.74), is much smaller and less significant than that calculated from the main sample, 2.38% (t-statistic: 5.58; compare columns (1)–(3) in Tables 4 and IA.6). The lower early exercise risk premium estimated from the closer-to-maturity sample is noteworthy since our theory would predict that premium to be higher. In the same vein, the effects of the put and stock characteristics on the spread return across those option types obtained from FM regressions are much weaker in the closer-to-maturity than the sample used in our main paper (compare Panels A across Tables 7 and IA.7). Given those findings, we believe it to be more prudent to rely on the sold-before-maturity calendar-month returns rather than returns measured over some closer-to-maturity period in our main empirical work.

IA.6 Option-Price-Weighted Portfolios

Following other studies, we look into equally-weighted double-sorted moneyness and time-to-maturity as well as equally-weighted univariate idiosyncratic stock volatility portfolios in our empirical tests in Section 3.3.2 of our main paper. To alleviate concerns that the returns of those portfolios could be biased due to market microstructure issues arising from low prices (see Asparouhova et al. (2010; 2013)), we next however also evaluate their corresponding option-price-weighted counterparts. To do so, we use the traded American (synthetic European) put price at the start of the return period to form price-weighted American (European) put portfolios. We then also form spread portfolios long a price-weighted American and short its corresponding price-weighted European put portfolio.

Using a design identical to Table 5 in our main paper, Table IA.8 gives the results from the price-weighted double-sorted moneyness and time-to-maturity portfolios. The table shows that, in comparison to the equally-weighted portfolios, the price-weighted portfolios generate more positive early exercise risk premium estimates. Specifically, while the mean monthly returns of the spread portfolios long equally-weighted optimally-early-exercised American and short their equally-weighted equivalent European puts can reach up to 6.29% (t-statistic: 6.65), the corresponding number for the price-weighted portfolios is 8.59% (t-statistic: 7.08; see columns (1)–(3) in Tables 5 and IA.8). In addition, the price-weighted portfolios also suggest a more positive (negative) effect of moneyness (time-to-maturity) on the early exercise risk premium. Considering only 60-90 day puts, the mean spread return across optimally-early-exercised American and their equivalent European puts rises, for example, from an insignificant –0.12% to 3.36% (t-statistic: 5.04) over the price-weighted moneyness portfolios, but only from an insignificant –0.32% to 2.26% (t-statistic: 4.16) over their equally-weighted counterparts (see again columns (1)–(3) in Tables 5 and IA.8). Finally, the mean spread return across never-early-exercised American and their equivalent European puts does not greatly differ across the equally-weighted and price-weighted portfolios (see columns (2)–(3) in the same tables).

TABLE IA.8 ABOUT HERE

Relying on a design identical to Table 6 in our main paper, Table IA.9 shows the results from the price-weighted univariate stock volatility portfolios controlling for moneyness. As before, the price-weighted portfolios generate more positive early exercise risk premium estimates than the corresponding equally-weighted portfolios. To be specific, while the mean monthly returns of the spread portfolios long equally-weighted optimally-early-exercised American and short their equally-weighted equivalent European puts can reach up to 4.39% (t-statistic: 7.37), the corresponding number for the price-weighted portfolios is 4.60% (t-statistic: 7.66; compare Tables 6 and IA.9). Notwithstanding, the drop in the early exercise risk premium estimates is marginally less pronounced over the price-weighted (4.03%; t-statistic: –7.46) rather than the equally-weighted (4.74%; t-statistic: –9.01) portfolios (see columns "High–Low" in these tables). Finally, the mean spread return across never-early-exercised American and their equivalent European puts does, once again, not greatly differ across the equally-weighted and price-weighted portfolios (compare Panels B in Tables 6 and IA.9).

TABLE IA.9 ABOUT HERE

Overall, this section reveals that option-price-weighted portfolios corroborate the main conclusions extracted from the equally-weighted portfolios studied in our main paper.

IA.7 The Raw Premium and the Interest Rate

In Section 3.3.3 of our main paper, we argue that the early exercise risk premium is expected to rise with the risk-free rate of return since a higher risk-free rate incentivizes put owners to early exercise their positions, especially when the puts have a higher optimal-early-exercise probability. We then write that we evaluate this prediction by relying on the sudden drop in the annual risk-free rate from an average of 3.59% until the start of 2008 to an average of 0.44% thereafter as exogenous shock, treating American puts with a high (low) optimal early exercise probability as treated (control) puts. While we only briefly summarize the main conclusions from these tests in our main paper to conserve space, we offer the full set of results in this section of the Internet Appendix.

Table IA.10 gives the results from repeating the double-sorted moneyness and time-to-maturity portfolio exercise in Table 5 in our main paper separately for the two subsample periods outlined above. While Panels A to C focus on ITM, ATM, and OTM puts, respectively, columns (1) to (2)–(1) ((3) to (4)–(3)) allow (do not allow) for optimal early exercises. In line with our reasoning, columns (1) to (2)–(1) reveal that, allowing for early exercises, the early exercise risk premium is markedly higher over the earlier (high risk-free rate) than later (low) subsample period, with the difference, however, only statistically and economically significant for the treated (i.e., high-early-exercise-probability) puts. While the mean spread return of 60-90 day ITM puts, for example, decreases by a significant 3.88% per month (t-statistic: –5.02) from the earlier to the later subperiod, the corresponding number for 60-90 day OTM puts is an only insignificant 0.15% (t-statistic: –0.20). Conversely, not allowing for optimal early exercises, columns (3) to (4)–(3) point to much weaker differences.

TABLE IA.10 ABOUT HERE

Overall, this section offers empirical evidence confirming our theoretical prediction that the early exercise risk premium rises with the risk-free interest rate.

IA.8 Short-Sale Constraints, Liquidity, and Dividends

We now investigate how violations of our main empirical assumptions affect our results. We first look into violations of the rule to never early exercise an American call on a zero-dividend stock as well as of put-call parity induced through short-selling constraints and/or illiquidity. We next turn to violations of the assumption that investors can ex-ante identify zero-dividend stocks.

IA.8.1. Optimal Early Exercise Rules and Put-Call Parity

Our empirical strategy crucially relies on the assumption that it is never optimal to early exercise an American call on a zero-dividend stock, allowing us to use such ("quasi-European") calls together with put-call parity to synthetically construct European puts. A valid concern with that strategy is that Jensen and Pedersen (2016) and Figlewski (2022) establish that stock short-selling constraints and stock and option transaction costs can lift the early exercise payoff of an American call on a zero-dividend stock above its alive value, making it optimal to early exercise that call. In the same vein, Cremers and Weinbaum (2010) demonstrate that higher transaction costs lead to larger deviations from put-call parity, rendering our synthetic European put prices less accurate.

We next validate that such violations of our empirical strategy do not bias our conclusions by conditioning our portfolio sorts on stock short-selling constraints and stock and option liquidity. We start with the stock short-selling constraints. Consistent with Jensen and Pedersen (2016), we use Markit's Daily-Cost-of-Borrow score (DCBS) to measure such constraints. The DCBS takes on an integer value from one to ten, with a higher value indicating greater short-selling constraints and stocks with a score equal to or below five considered as "easy-to-short."[8] Table IA.11 then shows the results from repeating the double-sorted moneyness and time-to-maturity portfolio exercise in Table 5 in our main paper separately on puts with an available DCBS (columns (1) and (3)) and

[8] Interestingly, Jensen and Pedersen (2016) report that less than one percent of all deep ITM American calls on zero-dividend stocks with a DCBS equal to or below five are early exercised, suggesting that investors closely follow the rule to never early exercise American calls on zero-dividend assets for that subsample.

those with a score equal to or below five ((2) and (4)).[9] For the sake of brevity, the table, however, only reports the mean spread returns across optimally-early-exercised American and their equivalent European puts (columns (1) to (2)) and never-early exercised American and the same European puts ((3) to (4)). Strikingly, the table demonstrates that stock short-selling constraints work against us finding a positive early exercise risk premium. To be more specific, columns (1) to (2) reveal that all mean spread returns involving optimally-early-exercised American puts rise upon us excluding hard-to-short-sell stocks. Conversely, all mean spread returns involving never-early-exercised American puts draw closer to zero and become insignificant upon us doing the same.

Table IA.11 About Here

We next look into the joint effect of stock short-selling constraints and stock and options liquidity on our results. To do so, we measure stock liquidity as one over the absolute daily return scaled by daily dollar trading volume averaged over the twelve months before the return period (see Amihud (2002)). Conversely, we measure option liquidity as one over an option's bid-ask spread scaled by its price or its open interest scaled by the underlying stock's dollar trading volume at the start of that period (see Cao and Han (2013) and Christoffersen et al. (2018)). Using only options on stocks with a DCBS equal to or below five, we sort our option pairs into three sets of univariate portfolios, the first (second) [third] based on the median liquidity of the American put (American call) [stock]. We finally use the intersection of those portfolios to create $2 \times 2 \times 2$ triple-sorted portfolios.

Table IA.12 gives the results from repeating the double-sorted moneyness and time-to-maturity portfolio exercise in Table 5 in our main paper separately on only put-pairs on easy-to-short-sell stocks in the top American put, top American call, and top stock liquidity portfolios ("high-liquidity assets;" columns (1) and (3)) and those in the corresponding bottom portfolios ("low-liquidity assets;" (2) and (4)). Just like before, columns (1) to (2) ((3) to (4)) of the table report the mean spread returns across optimally-early-exercised (never-early-exercised) American and their equivalent European puts. While Panel A uses the bid-ask spread to proxy for option liquidity, Panel B uses the open

[9]Due to DCBS data availability, we run our tests in Tables IA.11 and IA.12 on the 2004-2021 sample period.

interest. Remarkably, the table shows that stock and option illiquidity further work against us finding either a positive early exercise risk premium or the anticipated relations between the premium and the two put characteristics. While the mean monthly spread return involving optimally-early-exercised American puts can, for example, reach up to 8.17% (t-statistic: 4.03) in the low bid-ask spread/low Amihud (2002) value ("high liquidity") subsample, the corresponding number for the high bid-ask spread/high Amihud (2002) value ("low liquidity") subsample is only 6.00% (t-statistic: 4.72; compare columns (1) and (2) in Panel A). Moreover, the same spread return only rises with moneyness in the low but not the high bid-ask spread/Amihud (2002) value subsample (compare the same columns). Finally, the mean monthly spread return involving never-early-exercised American puts is usually close to zero and insignificant in both subsamples (see columns (3) and (4)).

TABLE IA.12 ABOUT HERE

IA.8.2. Identification of Zero-Dividend Stocks

Our empirical strategy also implicitly assumes that real investors are able to ex-ante identify zero-dividend stocks since only American calls on such stocks are equivalent to European calls. While we believe that investors are likely to be able to do so since most firms pay out dividends at the same points in a calendar year, extraordinary dividends are extremely rare, and dividends tend to be announced 3-4 weeks in advance, we now nonetheless dig deeper into that assumption. To do so, we repeat the double-sorted portfolio exercise in Table 5 of our main paper using only put pairs written on stocks projected to not pay out cash over their time-to-maturity. We identify stocks not projected to pay out cash over that time using Optionmetrics dividend projections.[10]

Using a design identical to Table 5 in our main paper, Table IA.13 gives the results from the double-sorted moneyness and time-to-maturity portfolio exercise excluding put pairs on stocks projected to pay out dividends (rather than those which did actually pay out dividends) over their time-to-

[10]Optionmetrics offers forecasts of a stock's discrete dividends at the end of each option trading day. They make those forecasts five years into the future based on the stock's past dividend pattern, using only information known as of the current date. In case of yet unannounced dividends, they use a proprietary extrapolation algorithm to create a set of projected ex-dividend dates according to the stock's usual dividend frequency.

maturity. The table demonstrates that excluding puts based on dividend projections rather than realizations does not greatly change our evidence, consistent with the observation that the dividend projections are extremely accurate (compare all columns in Tables 5 and IA.13).

TABLE IA.13 ABOUT HERE

In sum, the results in this section suggest that violations of the rule to never early exercise an American call on a zero-dividend stock as well as of put-call parity work against the conclusions established in our main paper. Moreover, violations of the assumption that investors are able to ex-ante identify zero-dividend stocks hardly affect those same conclusions.

IA.9 Bid-Ask Transaction Costs

We finally investigate whether real investors are able to earn the early exercise risk premium in single-stock put markets with transaction costs. To do so, we rely on the realistic option transaction cost estimates of Muravyev and Pearson (2020) for algorithmic traders and all traders (i.e., algorithmic and non-algorithmic traders). While algorithmic traders time their trades to ensure that they buy (sell) when the expected midpoint price (i.e., the true option value) is close to the current ask (bid) price, non-algorithmic traders do not engage in timing. The upshot is that algorithmic traders incur much lower transaction costs than non-algorithmic traders. In our tests, we use the transaction cost estimates from Panel B of Table 5 in Muravyev and Pearson (2020), which reports them not only separately for algorithmic and all traders but also for ITM, ATM, and OTM options.

Table IA.14 gives the results from the moneyness and time-to-maturity double portfolio sorts incorporating transaction costs run on all put pairs (columns (1) to (3)) or only on high-liquidity pairs on stocks with a DCBS equal to or below five ((4) to (6)). While columns (1) and (4) show raw early exercise risk premium estimates, columns (2) and (5) ((3) and (6)) report those estimates adjusted for algorithmic-trader (all-trader) transaction costs. To adjust the estimates, we assume that investors buy (sell) at the midpoint option price plus (minus) S times the bid-ask spread, where we imply S from Muravyev and Pearson's (2020) estimates.[11] The table reveals that accounting for transaction costs greatly eats into our early exercise risk premium estimates. Despite that, even in the all-put-pairs sample, algorithmic traders can still earn a significantly positive monthly premium of 3.16% (t-statistic: 3.17) from 30-60 day ITM puts, but not from others (see column (2)). In contrast, column (3) demonstrates that the average trader is never able to earn a significant premium in that sample. Turning to the more liquid put sample, algorithmic traders can now earn a significant premium from 30-60 and 60-90 day ITM as well as from 30-60 day ATM puts (column (5)), while the average trader can still earn such a premium from 30-60 day ITM puts ((6)).

Table IA.14 About Here

Overall, this section suggests that transaction costs do not always eliminate the significantly positive early exercise risk premiums discovered in our main empirical tests. In particular, both algorithmic traders and average traders can still earn significantly positive premiums when trading in higher-liquidity short-time-to-maturity ITM/ATM puts on easier-to-short stocks.

[11] In particular, Muravyev and Pearson's (2020) evidence implies algorithmic-trader S values of 0.066, 0.102, and 0.182 and all-trader S values of 0.216, 0.258, and 0.301 for ITM, ATM, and OTM options, all respectively.

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Table IA.1: The SV-World Early Exercise Risk Premium: Comparative Statics

The table presents the spread in the expected raw return across equivalent American and European puts in the SV world under our basecase parameter values combined with either a high or a low value for each SV parameter within some selected set. The selected set of SV parameters contains the volatility of variance σ_v (Panel A), the physical variance mean reversion speed $\kappa^{\mathbb{P}}$ (Panel B), the correlation between asset value and variance ρ (Panel C), and the variance risk premium parameter γ (Panel D). We choose high values for these parameters in the upper subpanel of each panel and low values in the lower. Columns (1) to (3) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (4) to (6) at-the-money (ATM; 1.00), and columns (7) to (9) out-of-the-money (OTM; 0.95) puts. Conversely, we consider 30, 60, and 90 days-to-maturity puts in columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9), respectively. Finally, the first, second, and third row in each subpanel consider puts on an asset with an annualized volatility of 15%, 30%, and 45%, respectively. We describe the basecase parameter values in Section 2.2.1 of our main paper and the high and low values for the SV parameters in Section IA.2 of this Internet Appendix.

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Volatility of Variance, σ_v									
Panel A1: $\sigma_v = 0.60$									
15	7.47	3.32	1.78	2.65	0.41	0.09	1.09	0.02	−0.01
30	2.34	0.43	0.07	1.57	0.17	0.00	1.04	0.07	0.00
45	1.38	0.17	0.02	1.09	0.10	0.00	0.87	0.05	0.00
Panel A2: $\sigma_v = 0.20$									
15	7.08	2.62	1.08	3.45	0.50	0.07	1.51	0.05	−0.03
30	2.41	0.50	0.09	1.74	0.20	0.01	1.27	0.07	−0.01
45	1.42	0.21	0.02	1.12	0.11	0.00	0.90	0.05	0.00
Panel B: Physical Variance Mean Reversion Speed, $\kappa^{\mathbb{P}}$									
Panel B1: $\kappa^{\mathbb{P}}$ *= 10*									
15	7.24	2.82	1.24	3.23	0.56	0.12	1.39	0.09	−0.02
30	2.40	0.49	0.09	1.70	0.20	0.02	1.21	0.08	0.00
45	1.41	0.20	0.03	1.11	0.11	0.00	0.89	0.05	0.00
Panel B2: $\kappa^{\mathbb{P}}$ *= 2*									
15	7.32	3.10	1.67	2.96	0.42	0.05	1.23	0.03	−0.01
30	2.37	0.45	0.07	1.64	0.17	0.01	1.15	0.06	0.00
45	1.39	0.18	0.02	1.10	0.09	0.00	0.88	0.05	0.00
Panel C: Correlation, ρ									
Panel C1: $\rho = -0.10$									
15	6.98	2.70	1.20	3.17	0.48	0.08	1.35	0.04	−0.02
30	2.38	0.45	0.07	1.68	0.19	0.01	1.20	0.07	0.00
45	1.40	0.20	0.02	1.11	0.10	0.00	0.94	0.05	0.00
Panel C2: $\rho = -0.50$									
15	7.88	3.37	1.67	3.08	0.60	0.15	1.30	0.08	0.00
30	2.42	0.52	0.12	1.68	0.22	0.02	1.14	0.06	0.00
45	1.41	0.22	0.03	1.09	0.12	0.00	0.90	0.05	0.00

(continued on next page)

Table IA.1: The SV-World Early Exercise Risk Premium: Comparative Statics (cont.)

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel D: Variance Risk Premium Parameter, γ									
Panel D1: $\gamma = 0.00$									
15	7.40	3.15	1.59	3.22	0.60	0.16	1.38	0.09	-0.02
30	2.40	0.52	0.12	1.70	0.21	0.02	1.22	0.08	0.00
45	1.40	0.21	0.04	1.12	0.12	0.01	0.90	0.06	0.00
Panel D2: $\gamma = -12.00$									
15	7.04	2.47	0.97	2.93	0.38	0.04	1.20	0.03	-0.01
30	2.31	0.37	0.04	1.61	0.15	0.00	1.11	0.05	0.00
45	1.39	0.15	0.01	1.08	0.08	0.00	0.88	0.04	0.00

Table IA.2: The SVJ-World Early Exercise Risk Premium: Comparative Statics

The table presents the spread in the expected raw return across equivalent American and European puts in the SVJ world under our basecase parameter values combined with either a high or a low value for each SVJ parameter within some selected set. The selected set of SVJ parameters contains the physical jump intensity $\lambda^{\mathbb{P}}$ (Panel A), the physical mean jump size $\mu_z^{\mathbb{P}}$ (Panel B), the difference in the physical and risk-neutral jump intensity (jump intensity risk $\lambda^{\mathbb{Q}} \geq \lambda^{\mathbb{P}}$; Panel C), and the difference in the physical and risk-neutral mean jump size (jump size risk $\mu_z^{\mathbb{Q}} \leq \mu_z^{\mathbb{P}}$; Panel D). We choose high values for these parameters in the upper subpanel of each panel and low values in the lower. Columns (1) to (3) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (4) to (6) at-the-money (ATM; 1.00), and columns (7) to (9) out-of-the-money (OTM; 0.95) puts. Conversely, we consider 30, 60, and 90 days-to-maturity puts in columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9), respectively. Finally, the first, second, and third row in each subpanel consider puts on an asset with an annualized volatility of 15%, 30%, and 45%, respectively. We describe the basecase parameter values in Section 2.2.1 of our main paper and the high and low values for the SVJ parameters in Section IA.2 in this Internet Appendix.

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Physical Jump Intensity, $\lambda^{\mathbb{P}}$									
Panel A1: $\lambda^{\mathbb{P}} = 6.00$									
15	2.87	0.98	0.40	0.99	0.21	0.07	0.47	0.06	0.00
30	1.83	0.40	0.09	1.25	0.18	0.03	0.83	0.10	0.02
45	1.26	0.17	0.02	1.01	0.10	0.01	0.81	0.06	0.00
Panel A2: $\lambda^{\mathbb{P}} = 0.50$									
15	6.34	2.90	1.50	2.90	0.61	0.17	1.10	0.09	0.01
30	2.39	0.45	0.10	1.70	0.22	0.01	1.25	0.07	0.00
45	1.42	0.18	0.02	1.14	0.12	0.00	0.92	0.05	0.00
Panel B: Physical Mean Jump Size, $\mu_z^{\mathbb{P}}$									
Panel B1: $\mu_z^{\mathbb{P}} = 0.05$									
15	4.16	1.32	0.48	1.30	0.31	0.07	0.71	0.06	−0.02
30	2.04	0.44	0.10	1.41	0.24	0.05	0.88	0.09	0.02
45	1.35	0.20	0.02	1.07	0.12	0.00	0.82	0.06	0.00
Panel B2: $\mu_z^{\mathbb{P}} = -0.02$									
15	2.46	1.10	0.59	1.10	0.22	0.05	0.48	0.06	0.00
30	1.81	0.38	0.09	1.26	0.18	0.01	0.90	0.06	−0.01
45	1.24	0.18	0.02	1.00	0.11	0.00	0.76	0.06	0.00
Panel C: Jump Intensity Risk ($\lambda^{\mathbb{Q}} \geq \lambda^{\mathbb{P}}$)									
Panel C1: $\lambda^{\mathbb{Q}} = 2 \times \lambda^{\mathbb{P}}$									
15	3.23	0.81	0.20	0.96	0.09	−0.02	0.44	−0.02	−0.04
30	1.90	0.35	0.05	1.32	0.16	0.02	0.92	0.08	0.02
45	1.31	0.16	0.00	1.08	0.10	0.00	0.89	0.06	0.00
Panel C2: $\lambda^{\mathbb{Q}} = 1 \times \lambda^{\mathbb{P}}$									
15	4.34	1.98	0.94	1.68	0.44	0.15	0.78	0.12	0.04
30	2.09	0.47	0.11	1.47	0.22	0.04	1.09	0.11	0.02
45	1.33	0.19	0.02	1.08	0.12	0.01	0.88	0.06	0.00

(continued on next page)

Table IA.2: The SVJ-World Early Exercise Risk Premium: Comparative Statics (cont.)

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel D: Jump Size Risk ($\mu_z^{\mathbb{Q}} \leq \mu_z^{\mathbb{P}}$)									
Panel D1: $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}}$									
15	3.49	1.29	0.63	2.02	0.47	0.20	1.39	0.20	0.08
30	2.16	0.41	0.08	1.59	0.20	0.02	1.20	0.08	0.00
45	1.37	0.19	0.02	1.11	0.12	0.01	0.87	0.06	0.00
Panel D2: $\mu_z^{\mathbb{Q}} = \mu_z^{\mathbb{P}} - 0.08$									
15	3.52	0.85	0.11	0.61	−0.06	−0.16	0.15	−0.18	−0.15
30	1.85	0.36	0.05	1.16	0.18	0.03	0.65	0.06	0.01
45	1.27	0.18	0.01	1.01	0.11	0.00	0.75	0.05	0.00

Table IA.3: The SV-World Early Exercise Risk Premium in Stock Index Puts

The table presents the spread in the expected raw return between equivalent American and European puts in the SV world calibrated to the S&P 500 estimates in Bates (2000; Panel A), Eraker (2004; Panel B), Hurn et al. (2015; Panel C), and Jacobs and Liu (2019; Panel D). We show the SV estimates in the panel headings. Columns (1) to (3) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (4) to (6) at-the-money (ATM; 1.00), and columns (7) to (9) out-of-the-money (OTM; 0.95) puts. Conversely, we consider 30, 60, and 90 days-to-maturity puts in columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9), respectively. Finally, the first, second, and third row in each panel consider puts on an asset with an annualized volatility of 15%, 30%, and 45%, respectively.

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Bates (2000); Period: 1988-1993; $\kappa^{\mathbb{P}} = 1.26$, $\sigma_v = 0.69$, $\rho = -0.59$, $\gamma = -4.73$									
15	10.41	5.92	4.49	2.01	0.04	−0.01	0.92	0.01	0.01
30	2.24	0.30	0.01	1.39	0.09	0.02	0.89	0.04	0.02
45	1.34	0.13	0.00	1.00	0.04	0.01	0.76	0.03	0.01
Panel B: Eraker (2004); Period: 1987-1990; $\kappa^{\mathbb{P}} = 4.79$, $\sigma_v = 0.55$, $\rho = -0.57$, $\gamma = -8.21$									
15	8.51	3.57	1.67	2.52	0.34	0.07	1.06	0.04	0.02
30	2.30	0.38	0.05	1.51	0.14	0.01	0.98	0.06	0.01
45	1.38	0.16	0.00	1.05	0.08	0.00	0.80	0.04	0.01
Panel C: Hurn et al. (2015); Period: 1990-2007; $\kappa^{\mathbb{P}} = 1.88$, $\sigma_v = 0.39$, $\rho = -0.74$, $\gamma = -13.35$									
15	8.55	3.18	1.17	2.72	0.31	0.03	1.17	0.02	0.02
30	2.30	0.36	0.03	1.52	0.14	0.01	1.01	0.05	0.01
45	1.33	0.15	0.00	1.03	0.07	0.01	0.85	0.03	0.01
Panel D: Jacobs and Liu (2019); Period: 1996-2015; $\kappa^{\mathbb{P}} = 2.16$, $\sigma_v = 0.43$, $\rho = -0.92$, $\gamma = -5.97$									
15	11.09	5.07	2.51	2.85	0.44	0.07	1.28	0.04	0.02
30	2.36	0.46	0.09	1.56	0.18	0.01	1.09	0.05	0.01
45	1.38	0.18	0.01	1.06	0.10	0.00	0.84	0.04	0.01

Table IA.4: The SVJ-World Early Exercise Risk Premium in Stock Index Puts

The table presents the spread in the expected raw return between equivalent American and European puts in the SVJ world calibrated to the S&P 500 estimates in Eraker (2004; Panel A), Broadie et al. (2009; Panel B), Hurn et al. (2015; Panel C), and Jacobs and Liu (2019; Panel D). We show the SVJ estimates in the panel headings. Columns (1) to (3) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (4) to (6) at-the-money (ATM; 1.00), and columns (7) to (9) out-of-the-money (OTM; 0.95) puts. Conversely, we consider 30, 60, and 90 days-to-maturity puts in columns (1), (4), and (7); (2), (5), and (8); and (3), (6), and (9), respectively. Finally, the first, second, and third row in each panel consider puts on an asset with an annualized volatility of 15%, 30%, and 45%, respectively.

Vol.	ITM Puts Days-to-Maturity			ATM Puts Days-to-Maturity			OTM Puts Days-to-Maturity		
(%)	30	60	90	30	60	90	30	60	90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Eraker (2004); Period: 1987-1990									
$\kappa^{\mathbb{P}} = 4.79$, $\sigma_v = 0.51$, $\rho = -0.59$, $\gamma = -7.69$, $\lambda^{\mathbb{P}} = \lambda^{\mathbb{Q}} = 0.50$, $\mu_z^{\mathbb{P}} = -0.01$, $\mu_z^{\mathbb{Q}} = -0.05$, $\sigma_z^{\mathbb{P}} = \sigma_z^{\mathbb{Q}} = 0.17$									
15	4.54	2.24	1.42	1.60	0.45	0.24	0.71	0.20	0.11
30	2.04	0.51	0.18	1.33	0.27	0.08	0.86	0.15	0.05
45	1.31	0.21	0.03	1.03	0.13	0.02	0.79	0.10	0.01
Panel B: Broadie et al. (2009); Period: 1987-2005									
$\kappa^{\mathbb{P}} = 5.33$, $\sigma_v = 0.14$, $\rho = -0.52$, $\gamma = -10.00$, $\lambda^{\mathbb{P}} = 0.91$, $\lambda^{\mathbb{Q}} = 1.25$, $\mu_z^{\mathbb{P}} = -0.03$, $\mu_z^{\mathbb{Q}} = -0.05$, $\sigma_z^{\mathbb{P}} = \sigma_z^{\mathbb{Q}} = 0.07$									
15	5.68	2.17	0.89	2.11	0.42	0.07	0.66	0.05	−0.05
30	2.33	0.51	0.13	1.64	0.26	0.04	1.09	0.10	0.02
45	1.39	0.19	0.03	1.16	0.13	0.01	0.89	0.08	0.00
Panel C: Hurn et al. (2015); Period: 1990-2007									
$\kappa^{\mathbb{P}} = 1.71$, $\sigma_v = 0.65$, $\rho = -0.74$, $\gamma = -3.04$, $\lambda^{\mathbb{P}} = 2.33$, $\lambda^{\mathbb{Q}} = 2.83$, $\mu_z^{\mathbb{P}} = \mu_z^{\mathbb{Q}} = -0.02$, $\sigma_z^{\mathbb{P}} = \sigma_z^{\mathbb{Q}} = 0.02$									
15	11.14	5.56	3.52	2.58	0.40	0.06	1.11	0.03	0.00
30	2.24	0.43	0.08	1.48	0.17	0.02	0.97	0.05	0.01
45	1.31	0.16	0.02	1.02	0.10	0.00	0.75	0.04	0.01
Panel D: Jacobs and Liu (2019); Period: 1996-2015									
$\kappa^{\mathbb{P}} = 1.55$, $\sigma_v = 0.42$, $\rho = -0.94$, $\gamma = -3.34$, $\lambda^{\mathbb{P}} = \lambda^{\mathbb{Q}} = 0.89$, $\mu_z^{\mathbb{P}} = -0.01$, $\mu_z^{\mathbb{Q}} = -0.04$, $\sigma_z^{\mathbb{P}} = \sigma_z^{\mathbb{Q}} = 0.05$									
15	8.92	4.14	2.09	2.63	0.55	0.21	1.23	0.15	0.09
30	2.35	0.47	0.11	1.53	0.18	0.02	1.00	0.05	0.00
45	1.34	0.17	0.02	1.05	0.10	0.00	0.81	0.03	0.00

Table IA.5: The Effects of the Optimal Early Exercise Rule Approximation

The table offers the early exercise risk premium obtained from our simulations assuming that an optimal early exercise occurs if the underlying asset value comes within a 5% distance to the optimal early exercise threshold ("Appr.;" optimal early exercise rule approximation) or if the underlying asset value crosses the optimal early exercise threshold from above ("Exact;" exact optimal early exercise rule) plus the difference in these premiums ("Diff.") in the GBM (Panel A), SV (Panel B), and SVJ (Panel C) worlds. Columns (1), (2), and (1)–(2) consider in-the-money (ITM; strike-to-stock price = 1.05), columns (3), (4), and (3)–(4) at-the-money (ATM; 1.00), and columns (5), (6), and (5)–(6) out-of-the-money (OTM; 0.95) puts. Within each moneyness class, we consider puts with 30, 60, and 90 days-to-maturity. Within each maturity class, we finally consider puts on an asset with an annualized volatility of 15%, 30%, and 45%. Each simulation relies on five million asset-value paths with a number of time steps equal to the days-to-maturity. We describe the basecase parameter values used in the simulations in Section 2.2.1 of our main paper.

Days	Vol.	Early Exercise Risk Premium (in %)								
to	Vol.	ITM Puts			ATM Puts			OTM Puts		
Mat.	(%)	Appr.	Exact	Diff.	Appr.	Exact	Diff.	Appr.	Exact	Diff.
		(1)	(2)	(1)−(2)	(3)	(4)	(3)−(4)	(5)	(6)	(5)−(6)
Panel A: Geometric Brownian Motion (GBM) Model										
30	15	6.93	6.82	0.11	3.72	3.66	0.07	1.81	1.79	0.02
	30	2.47	2.45	0.02	1.84	1.83	0.02	1.40	1.39	0.01
	45	1.44	1.43	0.00	1.21	1.20	0.00	1.02	1.02	0.00
60	15	2.48	2.43	0.06	0.48	0.47	0.01	0.01	0.01	0.00
	30	0.45	0.45	0.00	0.18	0.19	−0.01	0.05	0.05	0.00
	45	0.19	0.20	−0.01	0.10	0.12	−0.02	0.04	0.06	−0.02
90	15	0.95	0.92	0.03	0.04	0.04	0.00	−0.03	−0.03	0.00
	30	0.08	0.08	0.00	0.01	0.01	0.00	−0.01	−0.01	0.00
	45	0.02	0.03	−0.01	0.00	0.02	−0.01	0.00	0.00	0.00
Panel B: Stochastic Volatility (SV) Model										
30	15	7.41	7.28	0.13	3.17	3.12	0.04	1.32	1.31	0.01
	30	2.40	2.38	0.02	1.69	1.68	0.01	1.19	1.19	0.01
	45	1.41	1.40	0.01	1.11	1.11	0.00	0.89	0.88	0.01
60	15	3.00	2.93	0.07	0.52	0.52	0.00	0.07	0.07	0.00
	30	0.48	0.48	0.00	0.18	0.19	−0.01	0.07	0.07	0.00
	45	0.18	0.19	−0.01	0.09	0.10	−0.01	0.05	0.05	−0.01
90	15	1.40	1.37	0.03	0.12	0.12	0.00	−0.02	−0.02	0.00
	30	0.08	0.08	0.00	0.01	0.01	0.00	−0.01	−0.01	0.00
	45	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel C: Stochastic Volatility-Jump (SVJ) Model										
30	15	4.13	4.03	0.10	1.44	1.42	0.03	0.57	0.56	0.01
	30	2.11	2.08	0.03	1.45	1.43	0.01	0.94	0.94	0.00
	45	1.35	1.34	0.01	1.09	1.09	0.00	0.81	0.83	−0.01
60	15	1.62	1.59	0.04	0.32	0.31	0.01	0.05	0.05	0.00
	30	0.44	0.45	0.00	0.20	0.21	0.00	0.06	0.07	−0.01
	45	0.18	0.19	−0.01	0.11	0.11	−0.01	0.05	0.05	−0.01
90	15	0.70	0.70	0.01	0.06	0.06	0.00	0.00	0.00	0.00
	30	0.09	0.10	−0.01	0.02	0.03	−0.01	0.00	0.00	0.00
	45	0.02	0.02	0.00	0.00	0.00	0.00	−0.01	−0.01	0.00

Table IA.6: Descriptive Statistics for the Closer-to-Maturity Return Sample

The table presents descriptive statistics for the monthly raw returns of optimally-early-exercised American puts (column (1)), never-early-exercised American puts ((2)), and synthetic European puts ((3)) as well as for the monthly raw returns of spread portfolios long an optimally-early-exercised American put and short its equivalent synthetic European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American put and short its equivalent synthetic European put ((2)–(3)). In contrast to the calendar-month returns used in our main paper, the returns studied in this table are computed over the four-week period from the week before expiration in month $t-1$ to the week before expiration in month t. The table also reports the moneyness (column (4)) and days-to-maturity ((5)) of the American and European put-pairs. The descriptive statistics include the mean, the standard deviation (StDev), the mean's t-statistic (Mean/StError), the bootstrapped 95% confidence interval for that t-statistic (95%BS-CI), several percentiles, and the total number of observations. We match the observations in columns (1), (2), and (3) along the moneyness and days-to-maturity dimension, so that each observation in one column corresponds to exactly one observation in another. We calculate moneyness as the ratio of strike price to stock price. With the exception of the t-statistic and the 95% confidence interval, we calculate each statistic as the time-series mean taken over the cross-sectional statistic.

	Monthly Put Return (%)			Monthly Spread Return (%)			Fundamentals	
	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE	Initial Money-ness	Initial Maturity Time
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)	(4)	(5)
Mean	−8.47	−10.80	−9.98	1.51	2.33	−0.82	1.00	82
StDev	68.49	68.71	75.27	32.94	28.74	13.43	0.09	35
Mean/StError	[−4.33]	[−5.34]	[−4.57]	[2.74]	[5.12]	[−4.01]		
95%BS-CI	{−2.12;1.82}	{−2.21;1.78}	{−2.23;1.77}	{−1.75;2.28}	{−1.84;2.10}	{−1.76;2.33}		
Percentile 1	−95.48	−95.55	−98.35	−92.77	−68.41	−46.15	0.81	38
Percentile 5	−87.47	−87.74	−91.87	−32.28	−17.32	−15.78	0.85	38
Quartile 1	−55.15	−56.63	−60.00	−3.94	−0.36	−2.48	0.94	47
Median	−21.06	−23.75	−24.46	0.59	0.00	0.31	1.00	81
Quartile 3	21.52	17.03	19.51	5.42	0.79	2.95	1.06	116
Percentile 95	111.13	108.99	119.72	41.73	35.05	11.70	1.15	131
Percentile 99	226.62	230.16	255.51	107.80	107.65	24.66	1.18	132
Observations	2,577	2,577	2,577	2,577	2,577	2,577	2,577	2,577

Table IA.7: Fama-MacBeth (1973) Regressions of the Closer-to-Maturity Spread Return on Moneyness, Days-to-Maturity, and Idiosyncratic Stock Volatility

The table presents the results of Fama-MacBeth (1973) regressions of the month-t raw return of a spread portfolio long an American put and short its equivalent synthetic European put on subsets of stock and put characteristics measured at the start of the return period. In contrast to the calendar-month returns used in our main paper, the returns studied in this table are computed over the four-week period from the week before expiration in month $t-1$ to the week before expiration in month t. While Panel A allows for optimal early exercises of the American puts over the return period, Panel B does not do so. The characteristics include the strike-to-stock price ratio ("moneyness"), time-to-maturity (as fraction of a year), and annualized idiosyncratic stock volatility. We use the Fama-French (1993)-Carhart (1997) model estimated over the prior twelve months of daily data to obtain idiosyncratic stock volatility. The plain numbers are monthly premium estimates (in decimals), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	(1)	(2)	(3)	(4)
Panel A: Optimally-Early-Exercised American Puts				
Constant	0.02***	−0.10***	0.03***	−0.09***
	[2.50]	[−3.75]	[3.32]	[−3.22]
Moneyness		0.16***		0.16***
		[5.96]		[6.12]
Time-to-Maturity		−0.21***		−0.20***
		[−5.99]		[−5.75]
Idiosyncratic Volatility			−0.05***	−0.04***
			[−3.46]	[−2.99]
Panel B: Never-Early-Exercised American Puts				
Constant	−0.01***	−0.07***	0.00	−0.07***
	[−4.26]	[−3.84]	[−0.14]	[−3.50]
Moneyness		0.06***		0.07***
		[3.96]		[4.09]
Time-to-Maturity		0.00		0.00
		[−0.02]		[0.35]
Idiosyncratic Volatility			−0.02***	−0.02***
			[−3.62]	[−3.87]

Table IA.8: Price-Weighted Moneyness and Days-to-Maturity Portfolios

The table presents the mean raw returns of moneyness and days-to-maturity sorted optimally-early-exercised American (column (1)), never-early-exercised American ((2)), and synthetic European ((3)) put portfolios as well as of spread portfolios long an optimally-early-exercised American put and short its equivalent synthetic European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American and short its equivalent synthetic European put ((2)–(3)). In Panels A, B, and C, we consider in-the-money (strike-to-stock price > 1.05), at-the-money (0.95-1.05), and out-of-the-money (< 0.95) puts, respectively. Within each panel, we consider puts with a short (30-60 days), medium (60-90), and long (90-120) time-to-maturity. The double-sorted portfolios are formed as described in Table 5 of our main paper, except that the non-spread portfolios are weighted by the put price at the start of the return period. We match the observations in columns (1), (2), and (3), so that each observation in one column corresponds to exactly one observation in another. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Monthly Put Return (%)			Monthly Spread Return (%)		
Days-to-Maturity	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)
Panel A: In-The-Money (Strike/Stock > 1.05)						
30-60	−11.75***	−20.60***	−20.34***	8.59***	8.86***	−0.27***
	[−6.97]	[−8.95]	[−8.55]	[7.08]	[7.74]	[−2.63]
60-90	−7.97***	−11.64***	−11.34***	3.36***	3.67***	−0.30***
	[−5.29]	[−7.00]	[−6.67]	[5.04]	[5.75]	[−3.98]
90-120	−6.05***	−8.17***	−7.93***	1.88***	2.12***	−0.24***
	[−4.49]	[−5.72]	[−5.39]	[4.01]	[4.59]	[−3.61]
Panel B: At-The-Money (Strike/Stock 0.95-1.05)						
30-60	−12.95***	−18.76***	−18.37***	5.42***	5.81***	−0.39**
	[−4.65]	[−7.05]	[−6.49]	[6.93]	[7.80]	[−1.99]
60-90	−7.44***	−9.58***	−8.95***	1.51***	2.14***	−0.64***
	[−3.25]	[−4.54]	[−4.06]	[4.68]	[6.10]	[−4.49]
90-120	−5.49***	−6.39***	−5.82***	0.33*	0.90***	−0.57***
	[−3.00]	[−3.60]	[−3.11]	[1.66]	[5.01]	[−4.42]
Panel C: Out-Of-The-Money (Strike/Stock < 0.95)						
30-60	−8.09*	−12.56***	−10.44**	2.34***	4.47***	−2.13***
	[−2.00]	[−3.37]	[−2.51]	[2.45]	[5.40]	[−3.89]
60-90	−8.12**	−9.29***	−8.00**	−0.12	1.17***	−1.29***
	[−2.75]	[−3.30]	[−2.62]	[−0.36]	[4.36]	[−3.61]
90-120	−5.23*	−5.54**	−4.66*	−0.57**	0.32***	−0.88***
	[−2.08]	[−2.25]	[−1.74]	[−2.36]	[2.12]	[−3.21]

Table IA.9: Price-Weighted Idiosyncratic Volatility Portfolios

The table presents the mean raw returns of univariate stock-volatility-sorted American and synthetic European put portfolios as well as of spread portfolios long one of the American and short the corresponding European put portfolios controlling for moneyness. While Panel A allows for optimal early exercises of the American puts over the return period, Panel B does not do so. The univariate portfolios controlling for moneyness are formed as in Table 6 in our main paper, except that the underlying double portfolios are weighted by the option price at the start of the return period. We hold the portfolios over month t. We also form spread portfolios long the top and short the bottom quintile portfolio ("High–Low"). We match the American and European put observations, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Idiosyncratic Stock Volatility Quintile					
	1(Low)	2	3	4	5(High)	High–Low
Panel A: Optimally-Early-Exercised American Puts						
American Put	−10.64***	−9.63***	−7.86***	−6.19**	−6.87***	3.77*
	[−3.79]	[−3.79]	[−2.95]	[−2.42]	[−3.05]	[1.80]
European Put	−15.21***	−14.24***	−10.92***	−7.89***	−7.41***	7.80***
	[−5.16]	[−5.48]	[−3.91]	[−2.96]	[−3.11]	[3.17]
Spread	4.57***	4.60***	3.06***	1.71***	0.54	−4.03***
	[7.75]	[7.66]	[7.42]	[2.97]	[1.03]	[−7.46]
Panel B: Never-Early-Exercised American Puts						
American Put	−15.53***	−14.27***	−11.45***	−8.99***	−8.98***	6.56***
	[−5.76]	[−5.93]	[−4.38]	[−3.61]	[−4.02]	[2.90]
European Put	−15.21***	−14.24***	−10.92***	−7.89***	−7.41***	7.80***
	[−5.16]	[−5.48]	[−3.91]	[−2.96]	[−3.11]	[3.17]
Spread	−0.32	−0.04	−0.53***	−1.09***	−1.57***	−1.24***
	[−1.14]	[−0.15]	[−2.50]	[−4.58]	[−5.92]	[−3.79]
Mean Moneyness	1.001	1.002	1.002	1.002	1.002	

Table IA.10: Subperiod Tests

The table presents the mean monthly raw returns of moneyness and days-to-maturity sorted spread portfolios long an American and short the equivalent European put portfolio separately calculated over the January-1996 to December-2008 (columns (1) and (3)) and the January-2009 to December-2021 ((2) and (4)) subsample periods plus the differences in those returns between the subsample periods ((2)–(1) and (4)–(3)). While columns (1) to (2)–(1) allow for optimal early exercises of the American puts over the return period, columns (3) to (4)–(3) do not do so. In Panels A, B, and C, we consider in-the-money (strike-to-stock price ratio > 1.05), at-the-money (0.95-1.05), and out-of-the-money (< 0.95) puts, respectively. Within each panel, we further consider options with a short (30-60 days), medium (60-90), and long (90-120) time-to-maturity. See the caption of Table 5 for more details on the construction of the portfolios. We match the American and European puts, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Optimally-Early-Exercised American Puts			Never-Early-Exercised American Puts		
Days-to-Maturity	Until-2008	From-2009	Diff.	Until-2008	From-2009	Diff.
	(1)	(2)	(2)–(1)	(3)	(4)	(4)–(3)
Panel A: In-The-Money Puts (Strike/Stock > 1.05)						
30-60	9.20***	3.23***	−5.96***	−0.10	−0.67***	−0.57***
	[8.24]	[3.33]	[−4.05]	[−0.74]	[−4.51]	[−2.84]
60-90	4.15***	0.27	−3.88***	−0.14	−0.57***	−0.43***
	[8.03]	[0.48]	[−5.02]	[−1.42]	[−4.83]	[−2.83]
90-120	2.39***	−0.12	−2.51***	−0.22**	−0.43***	−0.21*
	[4.94]	[−0.37]	[−4.32]	[−2.12]	[−5.13]	[−1.68]
Panel B: At-The-Money Puts (Strike/Stock 0.95-1.05)						
30-60	6.06***	2.89***	−3.17***	−0.41	−0.64**	−0.23
	[7.43]	[2.89]	[−2.46]	[−1.28]	[−1.94]	[−0.52]
60-90	1.99***	0.45	−1.54***	−0.69***	−0.71***	−0.02
	[6.85]	[1.03]	[−2.93]	[−2.75]	[−2.95]	[−0.05]
90-120	0.51**	−0.10	−0.61**	−0.60***	−0.88***	−0.29
	[2.44]	[−0.35]	[−1.82]	[−2.71]	[−4.62]	[−1.05]
Panel C: Out-Of-The-Money Puts (Strike/Stock < 0.95)						
30-60	2.75***	0.38	−2.37	−1.60***	−3.32***	−1.72
	[3.99]	[0.26]	[−1.46]	[−2.25]	[−3.41]	[−1.42]
60-90	−0.24	−0.39	−0.15	−1.79***	−1.20**	0.59
	[−0.57]	[−0.64]	[−0.20]	[−2.75]	[−1.83]	[0.63]
90-120	−0.90**	−1.06**	−0.16	−1.21***	−1.44***	−0.23
	[−2.26]	[−2.24]	[−0.26]	[−2.44]	[−2.84]	[−0.33]

Table IA.11: Shorting Constraints and the Early Exercise Risk Premium

The table presents the mean raw returns of moneyness and days-to-maturity sorted spread portfolios long an American and short its equivalent European put constructed using either only puts on stocks with a non-missing Daily-Cost-of-Borrow score (columns (1) and (3)) or a score equal to or below five ((2) and (4)) at the start of the return period. While columns (1) and (2) allow for optimal early exercises of the American puts over the return period, columns (3) and (4) do not do so. In Panels A, B, and C, we consider in-the-money (strike-to-stock price > 1.05), at-the-money (0.95-1.05), and out-of-the-money (< 0.95) puts, respectively. Within each panel, we consider puts with a short (30-60 days), medium (60-90), and long (90-120) time-to-maturity. See the caption of Table 5 in our main paper for details on the construction of the portfolios. We match the American and European puts, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Optimally-Early-Exercised American Puts		Never-Early-Exercised American Puts	
Days-to-Maturity	Available DCBS	DCBS $\leq$ 5	Available DCBS	DCBS $\leq$ 5
	(1)	(2)	(3)	(4)
Panel A: In-The-Money (Strike/Stock > 1.05)				
30-60	5.62***	6.63***	−0.60***	−0.06
	[4.49]	[5.50]	[−3.69]	[−0.65]
60-90	1.83***	2.41***	−0.50***	−0.02
	[2.85]	[3.89]	[−4.16]	[−0.25]
90-120	0.94**	1.31***	−0.29***	0.01
	[2.11]	[3.09]	[−3.58]	[0.11]
Panel B: At-The-Money (Strike/Stock 0.95-1.05)				
30-60	4.12***	4.99***	−0.47*	0.30
	[4.99]	[6.48]	[−1.69]	[1.30]
60-90	1.15***	2.03***	−0.63***	0.19
	[2.88]	[5.81]	[−3.05]	[1.07]
90-120	0.25	0.77***	−0.52***	−0.04
	[0.98]	[3.24]	[−3.02]	[−0.25]
Panel C: Out-Of-The-Money (Strike/Stock < 0.95)				
30-60	1.28	3.03***	−2.40***	−0.86
	[0.95]	[2.75]	[−2.97]	[−1.26]
60-90	−0.38	0.94**	−1.09**	0.20
	[−0.83]	[2.23]	[−2.25]	[0.44]
90-120	−0.57*	0.38	−0.99***	−0.03
	[−1.72]	[1.66]	[−2.84]	[−0.12]

Table IA.12: Shorting Constraints, Liquidity, and the Early Exercise Risk Premium

The table presents the mean raw returns of moneyness and days-to-maturity sorted spread portfolios long an American and short its equivalent European put formed from puts on stocks with a Daily-Cost-of-Borrow score equal to or below five and within the top American call, top American put, and top stock (columns (1) and (3)) and the bottom American call, bottom American put, and bottom stock ((2) and (4)) liquidity portfolio at the start of the return period. While columns (1) and (2) allow for optimal early exercises of the American puts over the return period, columns (3) and (4) do not do so. We use the inverse of the scaled bid-ask spread (Panel A) or scaled open interest (Panel B) to proxy for put liquidity and the inverse of Amihud's (2002) measure to proxy for stock liquidity. In subpanels 1, 2, and 3, we consider in-the-money (strike-to-stock price > 1.05), at-the-money (0.95-1.05), and out-of-the-money (< 0.95) puts, respectively. Within each subpanel, we consider puts with a short (30-60 days), medium (60-90), and long (90-120) time-to-maturity. See the caption of Table 5 in our main paper (Section IA.8.1. in this Internet Appendix) for details on the construction of the moneyness and time-to-maturity portfolios (the triple-sorted liquidity portfolios). We match the American and European puts, so that each American put corresponds to exactly one European put. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Optimally-Early-Exercised American Puts		Never-Early-Exercised American Puts	
Days-to-Maturity	High Liquidity	Low Liquidity	High Liquidity	Low Liquidity
	(1)	(2)	(3)	(4)
Panel A: Option Liquidity Proxy: Bid-Ask Spread				
Panel A.1: In-The-Money (Strike/Stock > 1.05)				
30-60	8.17***	5.03***	0.00	−0.02
	[4.03]	[3.70]	[0.03]	[−0.12]
60-90	2.48**	1.95*	−0.04	−0.19
	[2.51]	[1.94]	[−0.42]	[−0.80]
90-120	1.41***	0.33	0.10	0.21
	[3.21]	[0.41]	[1.23]	[0.59]
Panel A.2: At-The-Money (Strike/Stock 0.95-1.05)				
30-60	5.69***	4.53***	0.49**	0.13
	[4.33]	[4.35]	[2.55]	[0.27]
60-90	1.64***	1.91**	−0.13	−0.04
	[2.85]	[1.87]	[−0.85]	[−0.08]
90-120	0.58	−0.14	0.01	−0.62
	[1.40]	[−0.22]	[0.07]	[−1.29]
Panel A.3: Out-Of-The-Money (Strike/Stock < 0.95)				
30-60	1.93	6.00***	−0.88	1.33
	[0.99]	[4.72]	[−1.08]	[1.44]
60-90	0.48	2.69**	0.04	1.39
	[0.85]	[2.22]	[0.09]	[1.37]
90-120	0.65*	0.19	0.44	−0.07
	[1.78]	[0.26]	[1.30]	[−0.09]
Panel B: Option Liquidity Proxy: Open Interest				
Panel B.1: In-The-Money (Strike/Stock > 1.05)				
30-60	6.49***	4.55***	0.01	−0.12
	[4.03]	[3.19]	[0.05]	[−1.13]
60-90	2.60**	2.13**	0.19	0.09
	[2.41]	[2.12]	[1.54]	[0.93]
90-120	0.95**	0.75	0.01	0.04
	[2.20]	[1.13]	[0.06]	[0.50]

(continued on next page)

Table IA.12: Shorting Cons., Liquidity, and the Early Exercise Risk Premium (cont.)

	Optimally-Early-Exercised American Puts		Never-Early-Exercised American Puts	
Days-to-Maturity	High Liquidity	Low Liquidity	High Liquidity	Low Liquidity
	(1)	(2)	(3)	(4)
		Panel B.2: At-The-Money (Strike/Stock 0.95-1.05)		
30-60	4.70***	4.43***	0.15	0.42**
	[4.45]	[3.55]	[0.56]	[2.72]
60-90	1.63***	1.17*	0.19	0.18
	[4.21]	[1.75]	[0.61]	[0.92]
90-120	0.62	0.70*	0.08	−0.06
	[1.38]	[1.70]	[0.25]	[−0.30]
		Panel B.3: Out-Of-The-Money (Strike/Stock < 0.95)		
30-60	−1.17	3.33**	−0.41	−1.51*
	[−0.57]	[2.04]	[−0.51]	[−1.39]
60-90	0.55	1.76*	1.13*	−0.46
	[0.78]	[1.95]	[1.85]	[−0.84]
90-120	−0.04	0.80	0.14	−0.15
	[−0.11]	[1.28]	[0.21]	[−0.40]

Table IA.13: Dividend Projections and the Early Exercise Risk Premium

The table presents the mean raw returns of moneyness and days-to-maturity sorted optimally-early-exercised American (column (1)), never-early-exercised American ((2)), and synthetic European ((3)) put portfolios as well as of spread portfolios long an optimally-early-exercised American put and short its equivalent European put ((1)–(3)), long an optimally and short its equivalent never-early-exercised American put ((1)–(2)), and long a never-early-exercised American and short its equivalent European put ((2)–(3)). We form the portfolios using only puts written on stocks projected to not pay out dividends over their maturity time. See the caption of Table 5 in our main paper for details on portfolio construction. We match the American and European put observations, so that each American put corresponds to exactly one European put. The plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Monthly Put Return (%)			Monthly Spread Return (%)		
Days-to-Maturity	Optimally Early-Exercised American (OEA)	Never Early-Exercised American (NEA)	Synthetic European (SE)	OEA Minus SE	OEA Minus NEA	NEA Minus SE
	(1)	(2)	(3)	(1)–(3)	(1)–(2)	(2)–(3)
			Panel A: In-The-Money (Strike/Stock > 1.05)			
30-60	−12.24***	−18.91***	−18.50***	6.26***	6.67***	−0.41***
	[−7.12]	[−9.00]	[−8.46]	[6.36]	[7.33]	[−3.26]
60-90	−7.71***	−10.36***	−10.00***	2.30***	2.65***	−0.36***
	[−5.29]	[−6.83]	[−6.38]	[4.04]	[5.05]	[−3.74]
90-120	−5.38***	−6.91***	−6.60***	1.22***	1.53***	−0.31***
	[−4.19]	[−5.28]	[−4.86]	[3.10]	[4.13]	[−4.01]
			Panel B: At-The-Money (Strike/Stock 0.95-1.05)			
30-60	−11.25***	−16.27***	−15.68***	4.43***	5.02***	−0.59***
	[−4.12]	[−6.27]	[−5.64]	[6.04]	[7.16]	[−2.52]
60-90	−6.89***	−8.88***	−8.14***	1.24***	1.99***	−0.75***
	[−3.16]	[−4.43]	[−3.83]	[3.94]	[6.40]	[−4.28]
90-120	−4.54**	−5.54***	−4.79**	0.25	1.00***	−0.75***
	[−2.56]	[−3.24]	[−2.61]	[1.23]	[5.56]	[−4.80]
			Panel C: Out-Of-The-Money (Strike/Stock < 0.95)			
30-60	−6.27	−10.41**	−7.76*	1.49*	4.15***	−2.65***
	[−1.59]	[−2.85]	[−1.88]	[1.70]	[6.00]	[−4.23]
60-90	−6.54**	−7.75**	−6.17*	−0.38	1.21***	−1.58***
	[−2.20]	[−2.73]	[−1.94]	[−0.99]	[4.78]	[−3.54]
90-120	−3.80	−4.15	−2.82	−0.99***	0.35***	−1.34***
	[−1.54]	[−1.72]	[−1.05]	[−3.07]	[2.43]	[−3.75]

Table IA.14: Transaction Costs and the Early Exercise Risk Premium

The table presents the mean raw returns of moneyness and days-to-maturity sorted spread portfolios long an optimally-early-exercised American and short the equivalent European put portfolio under the assumption that investors always buy (sell) at the midpoint price plus (minus) S times the quoted bid-ask spread. In line with Murayev and Pearson (2020), we set S equal to zero (no-transaction-cost case), to 0.066, 0.102, and 0.183 for in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM) options (algorithmic-trader case), or to 0.216, 0.258, and 0.301 for ITM, ATM, and OTM options (all-trader case), all respectively. While columns (1) to (3) consider all put pairs, columns (4) to (6) consider those featuring only high liquidity assets and stocks with a Daily-Cost-of-Borrow score equal to or below five. Panels A, B, and C consider ITM (strike-to-stock price > 1.05), ATM (0.95-1.05), and OTM (< 0.95) puts, respectively. Within each panel, we consider puts with a short (30-60 days), medium (60-90), and long (90-120) time-to-maturity. See the caption of Table 5 in our main paper for details on portfolio construction. We match the observations in columns (1) to (3) and (4) to (6), so that each observation in one column corresponds to exactly one observation in another. Plain numbers are mean monthly portfolio returns (in %), while the numbers in square parentheses are Newey-West (1987) t-statistics with a twelve-month lag length. ***, **, and * indicate that the t-statistic of the corresponding parameter estimate lies outside of its bootstrapped 99%, 95%, and 90% confidence interval, respectively.

	Full Sample			High Liquidity and Low Short Sale Constraints Asset Subsample		
Days-to-Maturity	No Transaction Costs	Algo-Trader Transaction Costs	All Trader Transaction Costs	No Transaction Costs	Algo-Trader Transaction Costs	All Trader Transaction Costs
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: In-The-Money (Strike/Stock > 1.05)						
30-60	6.29***	3.16***	−1.62	8.17***	7.43***	5.43**
	[6.65]	[3.17]	[−1.37]	[4.03]	[3.49]	[2.50]
60-90	2.26***	−0.22	−4.71***	2.48**	1.93*	0.02
	[4.16]	[−0.35]	[−5.71]	[2.51]	[1.85]	[0.02]
90-120	1.16***	−1.33***	−6.10***	1.41***	0.65	−1.16**
	[3.04]	[−3.01]	[−9.56]	[3.21]	[1.32]	[−1.89]
Panel B: At-The-Money (Strike/Stock 0.95-1.05)						
30-60	4.47***	−3.42***	−15.58***	5.69***	2.65**	−1.27
	[6.26]	[−3.94]	[−9.57]	[4.33]	[2.25]	[−1.05]
60-90	1.22***	−5.77***	−15.84***	1.64***	−0.48	−3.68***
	[4.03]	[−11.30]	[−14.22]	[2.85]	[−0.80]	[−5.12]
90-120	0.21	−6.56***	−16.20***	0.58	−1.49***	−4.83***
	[1.12]	[−13.98]	[−12.96]	[1.40]	[−4.09]	[−11.16]
Panel C: Out-Of-The-Money (Strike/Stock < 0.95)						
30-60	1.57*	−28.25***	−52.87***	1.93	−5.36	−25.65***
	[1.88]	[−8.11]	[−7.00]	[0.99]	[−0.76]	[−4.54]
60-90	−0.32	−28.74***	−63.87***	0.48	−7.98***	−13.92***
	[−0.85]	[−9.52]	[−3.70]	[0.85]	[−9.75]	[−10.32]
90-120	−0.98***	−25.23***	−46.84***	0.65*	−7.51***	−13.01***
	[−3.12]	[−10.60]	[−6.91]	[1.78]	[−13.08]	[−13.38]