Early Exercise, Implied Volatility Spread and Future Stock Return: Jumps Bind Them All*

Ian Garrett[†]
Alliance Manchester Business School
ian.garrett@manchester.ac.uk

Adnan Gazi[‡]
University of Liverpool Management School
adnan.gazi@liverpool.ac.uk

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Abstract

We find that early exercise premiums of exchange-traded single-stock American puts, in excess of the GBM-world premium, can negatively predict future stock returns. Simulations suggest that asset-value jumps, especially the mean jump-size, can positively drive this excess premium, while jump-size can also negatively induce the implied volatility (IV) spread of equivalent American option-pairs. Empirically, controlling for the effect of jump-size in excess premiums, the premium loses its predictive power. Furthermore, controlling for the excess premium or jump-size, IV spreads' predictability shown in the literature also diminishes. Our evidence survives under alternative explanations like informed trading, stock mispricing or market frictions.

Keywords: Empirical asset pricing; cross-sectional option pricing; implied volatility spread; put options; early exercise; jumps.

JEL classification: G11, G12, G15.

[†] Accounting and Finance Division, Room 4.079 AMBS, Booth Street West, Manchester M15 6PB, UK, tel.: +44(0)161 275 4958.
[‡]Corresponding author, Accounting and Finance Group, Room 278, ULMS, Chatham St, Liverpool L69 7ZH, UK, tel.: +44(0)151 795 3641.

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1 Introduction

Unlike the European counterparts, early exercise allows American option holders to *optimally* exercise their positions early, before the maturity date of options, based on the favourable movement of underlying asset. Hence, optimal early exercises might contain important information about holders' expectation on future underlying asset value paths. Nevertheless, although well-explored in the theoretical literature, there has not been much empirical research showing the implications of such exercises on options or underlying asset markets.[1]

In this paper, we find that early exercises of a plain-vanilla put play significant role in predicting the cross-section of underlying stock returns. Why can we expect such predictability using put early exercises? To answer this question and motivate our study, we rely on several theoretical works. For instance, under the Black-Scholes (1973) framework, Carr et al. (1992) derive the value of an American put as its equivalent European value plus the early exercise premium of that put. Importantly, the early exercise premium in Carr et al. (1992) can be described as the product of the risk-free rate, put strike price and the probability that the underlying asset value would go below the optimal put early exercise threshold.[2] Under a generalized mixed jump-diffusion process, Pham (1997) essentially shows a similar expression for the put premium.[3] These two studies therefore indicate that various asset and option characteristics (such as option moneyness, time-to-maturity, underlying asset volatility or stochastic nature of the volatility) can shift the continuous asset value path below the optimal early exercise threshold. Interestingly, these studies further point that any discontinuous jumps

[1]The empirical trend could be due to the fact that while we need both American and equivalent European options to examine the impact of early exercises, exchange-traded options are overwhelmingly American. Nonetheless, relying on put-call parity to create *synthetic* European put, Aretz and Gazi (2023), for instance, show that optimal early exercises have important implications on American put returns.

[2]Optimal put early exercise threshold comprises a set of highest underlying asset values at each time point, before the put matures, at which the put is optimal to exercise early.

[3]The value of put early exercise premium in Pham (1997) comes from two channels. While, the first channel is essentially the same as the premium derived under Carr et al. (1992), there is a second channel, looking at the impact on the premium if the asset value bounces back from the early exercise to the continuation region. However, the impact of this latter channel is negligible, as pointed out in Pham (1997).

in the asset value can also trigger optimal early exercises as jumps (more specifically, negative jumps) have the ability to move that value below the optimal threshold.

Under the Black-Scholes based geometric Brownian motion (GBM) world, options are considered as redundant assets. Hence, put early exercises coming from the GBM-related factors, such as moneyness, time-to-maturity and asset volatility, should not carry any information about underlying asset's future movement. Nevertheless, as Carr et al. (1992) and Pham (1997) point, both stochastic volatility (SV) and discontinuous jumps can also drive the early exercise premium of the put, specifically, the part of the premium in excess of the GBM-world. As both these factors show predictability in the asset pricing literature (see Yan (2011), Baltussen et al. (2018) and Dierkes et al. (2023), for instance), they can thus induce any predictive power of the put early exercise premium we document in this paper.

We next conduct a simulation exercise using Longstaff and Schwartz's (2001) method and separately under a GBM, a SV, and a SV with asset-value jumps (SVJ) process for the underlying asset value paths to see the pattern of the put early exercise premium with SV and discontinuous jumps. While doing so, we also explore whether these two factors can play any role in explaining the implied volatility spread ("IV Spread") of equivalent American calls and puts,[4] which is a common option-based stock return predictor in the literature (see Bali and Hovakimian (2009), Cremers and Weinbaum (2010) and An et al. (2014), among many others). The motivation of such exercise comes from a recent study of Campbell et al. (2023) which, using a three-period Cox-Ross-Rubinstein (CRR; 1979) based binomial model,[5] shows that put early exercise premiums are negatively related with IV spreads due to the sensitivity of the American put with time-varying volatility. Our approach broadens the idea of Campbell et al. (2023) as we explore that same relationship through parameters directly linked with SV, with plausible parameter values from the literature and under a rigorous simulation setting. More importantly, we also examine the role of discontinuous jumps on the theoretical relationship

[4] Literature defines IV spread as the difference in equivalent call and put implied volatilities.

[5] CRR model considers a discretized version of the stochastic processes for underlying asset value paths.

between the IV spread and the put premium.

Using volatility-of-variance ("VoV") as a measure for the SV, and mean jump-size and jump-intensity as measures for asset-value jumps, our simulation exercise offers three stylized facts. First, although both SV and jumps can drive the magnitude of a put's early exercise premium, in excess of its GBM-world premium ("Excess Premium"), in line with the theory, the impact is significantly stronger for the mean jump-size than any other parameters. Second, put premiums are always negatively associated with IV spreads in the presence of SV and/or jumps, extending Campbell et al. (2023). And third, in a world with SV and/or jumps, the excess put premium monotonically falls (rises) with a higher SV (jumps). Both VoV and jumps are negatively related with future stock returns in the literature. Hence, if we observe a return predictability for excess premiums (IV spreads) and if that predictability comes from the SV, we would expect a positive (negative) association between excess premiums (IV spreads) and future stock returns. In contrast, if that same predictability is driven by jumps, there should be a negative (positive) relation between excess premiums (IV spreads) and future returns.

In our empirical work, we use exchange-traded American options written on single-stocks not paying any cash within options' maturity periods ("zero-dividend stocks"). We start by calculating the premiums and the IV spread for each individual option in our sample. To calculate the excess premium, we first recall that the total put early exercise premium is the difference between the traded American put price and its equivalent European price. We can however decompose that total premium into its components by simultaneously adding and subtracting the equivalent theoretical American put price under the GBM world. In that case, the excess premium would be the difference between the traded American put price and its equivalent GBM-world price, while the GBM premium would be the difference between that GBM-world price and its equivalent European price. Following OptionMetrics, we calculate the price of an American put under the GBM world using the CRR model. We finally calculate the IV spread as the difference in equivalent call and put implied volatilities;

both taken from OptionMetrics.

Armed with option-level premiums and IV spreads, we proceed to calculate the variables at the stock level. To obtain the premiums for a particular stock, we first weight each put written on that stock by put's outstanding open interest. The stock-level premiums are then the open-interest-weighted averages of the individual put premiums. To calculate the stock-level IV spread, we however sum the open interests of each equivalent call-put pair written on the stock, and then weight the individual option-level IV spreads based on this sum. The IV spread for a stock is the sum-of-open-interests-weighted average of its option-level IV spreads.

In our empirical work, we find that excess put early exercise premiums can significantly predict both equal and value-weighted future stock returns. The predictability, however, is negative; the "High–Low" spread portfolio univariately sorted on excess premiums, for example, generates an equal (value) weighted mean excess return of -1.18% (-0.70%) per month, with a t-statistic of -7.25 (-3.87). The negative relation further indicates that excess premiums might derive the predictability from stock-price jumps, and not from the SV, in line with our simulations. Indeed, double portfolio sort exercise using excess premiums and an ex-ante left-tail variation measure from Bollerslev and Todorov (2011) confirms that is the case. While the "High–Low" portfolio sorted on excess premiums at the "Low" jumps, for instance, generates an equal-weighted mean excess return of -0.51% per month, that same return is much higher (in absolute term), of -2.38%, at the "High" jumps. In contrast, the double sort exercise with the VoV measure from Baltussen et al. (2018) does not show such variation.

Although our double portfolio sorts establish a link between the return predictability of excess premiums and jumps, recalling our theoretical simulations, we however realize that the mean jump-size, and not the jump-intensity, is the main driver for any excess premium dynamics. Hence, we should be able to explain excess premium's return predictability using jumps better with a mean jump-size proxy, rather than any overall left-tail measure. To this end, we follow Yan (2011) and use the IV slope measure as a proxy for the mean jump-size.

We find that the excess premium is highly correlated with this proxy; mean cross-sectional correlation between these two is around 60%. More interestingly, when we decompose the excess premium into a jump and a non-jump part, the non-jump part does not show any predictability, suggesting that excess premiums mainly derive predictive power from their ability to capture jump-size of the underlying stock, in complete agreement with our simulations.

We finally explore whether a jump-based explanation possess any merit in the return predictability of IV spreads shown in the literature. Doing such is interesting because while documenting that predictability, the literature is mostly divided on its source. For instance, although Campbell et al. (2023) indicate that IV spreads predicting stock returns is due to the spread capturing the time-varying volatility effect on American put early exercises, Cremers and Weinbaum (2010) suggest an informational route − from options to the stock market − flowing from informed investors. Conversely, Goncalves-Pinto et al. (2020) highlight a stock mispricing channel, while Hiraki and Skiadopolous (2023) identify a market friction channel. In contrast, our simulation exercise offers direct evidence that jumps can theoretically induce both excess premiums and IV spreads, and can create a mechanical relationship between these two. In our data sample, the mean cross-sectional correlation between IV spreads and excess premiums is −76%, consistent with the jump-based explanation. Importantly, when we orthogonalize IV spreads from the effect of excess premiums, the orthogonalized part loses its predictive power, suggesting that the excess premium, and ultimately jumps, play key role in explaining the return predictability in IV spreads. Our evidence on excess premiums' predictability, and the role of jumps in explaining both excess premiums' and IV spreads' predictive power survive even if we control for those alternative channels mentioned in the literature.

Our work adds to the empirical strand of literature studying the implications of option-based variables on future stock returns. Cremers and Weinbaum (2010) and An et al. (2014) show the return predictability using option-implied volatilities and IV spreads. In Bali and Hovakimian (2009), the predictor variable is the difference between stock's realized and implied volatilities.

In contrast, Conrad et al. (2013), Chordia et al. (2021) and Alexiou and Rompolis (2022) show that option-implied moments can also predict future returns. We contribute to this literature by identifying a new predictor: the excess put early exercise premium. We show that the return predictability for this premium is derived from its ability to capture large asset-value shocks. Indeed, by linking the predictability with jumps, we further complement the long-standing literature showing that various jump dynamics, including the systematic and idiosyncratic part of those dynamics, are priced in the stock market (see, e.g, Yan (2011), Cremers et al. (2015), Lu and Murray (2019) and Kapadia and Zekhnini (2019)).[6] We also contribute by looking into the drivers of IV spreads' return predictability. Our work differs from the previous literature as we look into the jump-based explanation for this predictability.

Finally, our work shares the same spirit with Valkanov et al. (2022) in showing that early exercises contain valuable information about future underlying asset value paths. Nevertheless, the predictability in Valkanov et al. (2022) is for daily index returns, using the total premium of index calls. In contrast, we present the cross-sectional predictability, using the *excess* premium of single-stock puts. Additionally, the finding in Valkanov et al. (2022) is based on the ability of call premiums to capture investors' dividend expectations, while our excess put premiums derive the predictability from their ability to capture jumps in underlying stocks.

We organise the paper as follows. Section 2 discusses our simulation exercise, while Section 3 offers the data and methodology. In section 4, we document our empirical evidence. Section 5 finally concludes.

2 Simulation Exercise

In this section, we offer a Monte-Carlo based simulation evidence to show that variations in jumps and SV can theoretically drive the early exercise premium of a put and the IV spread of an equivalent American call-put pair.

[6] For a review of the current development in jump literature, see, for instance, Dierkes et al. (2023).

2.1 Calculating the Early Exercise Premium and the IV Spread

We rely on Longstaff and Schwartz's (2001) least squares Monte-Carlo (LSM) method to simulate the underlying asset value paths, and then calculate the American values using those paths. To simulate the asset value paths assuming no dividend ("non-dividend asset"), we separately undertake a GBM process, a SV process from Heston (1993) and a SVJ process from Bates (1996). Under the risk-neutral $\mathbb{Q}$-probability measure, we can, for instance, write the instantaneous asset return and asset variance paths using the SVJ process as follows:

$$\frac{dS_t}{S_t} = (r - \lambda\widetilde{\bar{\mu}})dt + \sqrt{V_t}d\widetilde{W_t^S} + \left[e^{\widetilde{J_t^S}} - 1\right]d\widetilde{N}_t, \quad (1)$$

$$dV_t = \widetilde{\kappa}(\widetilde{\theta} - V_t)dt + \sigma_V\sqrt{V_t}d\widetilde{W_t^V}, \quad (2)$$

where S_t and V_t are, respectively, the value of the underlying asset and its variance at time t, r the risk-free rate, θ the long-term mean unconditional variance, κ the mean reversion speed for the instantaneous variance process, and σ_V the volatility of this variance process. W_t^S and W_t^V are separate Brownian motions, respectively for the asset return and its variance process, with $corr(dW_t^S, dW_t^V) = \rho$. Lastly, N_t is an independent Poisson process with a constant jump-intensity λ and random jumps J_t^S, where J_t^S is normally distributed, as $J_t^S \sim N(\mu_S, \sigma_S^2)$, and $\bar{\mu} = e^{\mu_S + \sigma_S^2/2} - 1$. Tildes ($\tilde{}$) over the parameters highlight that those values are drawn from the $\mathbb{Q}$-measure. Importantly, SVJ also nests other lower dimension processes: by setting the λ to zero, for instance, SVJ collapses to the SV process. In addition to that, by setting the κ and σ_V also equal to zero, SVJ further collapses to the GBM process.

To calculate the value of an American put under risk-neutral pricing framework, we then undertake the backward iteration approach from Longstaff and Schwartz (2001), and first identify the time-points at which the put can be optimal to early exercise, before its expiration. We start with put's maturity payoffs from all sample paths, $max(K - S_T, 0)$, where max is a maximum operator, K the strike price and S_T the path-specific $\mathbb{Q}$-measured underlying asset value at put maturity T. We next move back one time step, to $T-1$, where we run a OLS regression with discounted maturity payoffs on a higher-order polynomial function of underlying asset values from $T-1$.[7] We, however, only include observations from the in-the-money (ITM) paths to run this regression. At $T-1$, the path-specific continuation values are then simply the fitted values from the regression. Optimal early exercise occurs at $T-1$ if the early exercise payoff from a path at that time-point exceeds the continuation value. We continue in the same fashion, moving from $T-1$ to $T-2$, to $T-3$, until we reach the initial time t, always calculating the continuation value and comparing that value with the early exercise payoff to spot the optimal early exercise point at each time and path. Consequently, American put value is the mean of either discounted earliest exercise (if there are early exercises for a path), or maturity payoffs (if no such exercise) at t.

Unlike the American put, we however rely on closed-form solutions from Black-Scholes (1973), Heston (1993), and Bates (1996) to calculate the values of a European put, respectively, under a GBM, a SV, and a SVJ process. For American call, we recall that an American call written on a non-dividend asset is the same as a European call as it should not be exercised early, in accordance with Merton (1973). Hence, we also calculate the values of American call using closed-form solutions, same as the European call.

We next calculate the early exercise premium as the difference between the equivalent (same underlying asset, strike price and time-to-maturity) American and European put values. To measure the excess premium for an American put, we take the difference between its premium under the SV or SVJ world and its equivalent GBM-world premium. We further scale the premiums by their corresponding GBM-world American put values. Finally, to calculate the IV spread for an equivalent American call-put pair, we take their values under a specific stochastic process and transform them into their equivalent Black-Scholes IVs. The IV spread under that process is then simply the difference between the IVs of these two options.

[7] Following Longstaff and Schwartz (2001), we use up until the third-order Laguerre polynomials of the underlying asset value as regressors of this regression.

The base values of our simulations include: initial underlying asset value, S_0 of 50, option strike price, K of 50, risk-free rate, r of 3%, initial underlying asset volatility, $\sqrt{V_t}$ of 20%, and option time-to-maturity, T of 30 days. As we conduct our empirical tests using single-stock options, we rely on Pollastri et al. (2023) for SV and SVJ parameter values, which calibrates these values from single-stocks in the S&P 500.[8] Accordingly, we set the mean reversion speed, κ as 5.50, volatility-of-variance, σ_V as 40%, correlation coefficient, ρ as -0.25, annual jump-intensity, λ as 3.5, mean jump-size, μ_S as -3%, and jump-volatility, σ_S as 6%, based on the median values of these parameters from Pollastri et al. (2023). We however separately change the σ_V (as a measure for SV), and the μ_S and λ (as measures for jumps) from their 2.5th to 97.5th percentile values to see their effects on the early exercise premiums and IV spread. More specifically, we change σ_V from 20% to 60%, μ_S from 1% to -8% and λ from 1 to 6, all in small increments. Each of our simulation is based on five million asset value paths and on a daily frequency for the time interval.

2.2 The Premiums and the Spread with Stochastic Volatility and Jumps

Figure 1 shows the patterns of the put early exercise premiums and the IV spread of an equivalent American option pair, respectively, across the ranges of σ_V (Panel A), μ_S (Panel B) and λ (Panel C) parameter values. In Panel A (Panels B and C), we include the premium under the GBM world, along with the excess premium under the SV (SVJ) world. In all three panels, we show the dynamics of the premiums and the spread for at-the-money (ATM; strike-to-stock price ratio of 1.05) options only, while leaving that dynamics for in-the-money (ITM; 1.05) and out-of-the-money (OTM; 0.95) options for the internet appendix (IA).

[8]While Pollastri et al. (2023) calibrate parameters under the $\mathbb{P}$-measure, we require $\mathbb{Q}$-measure equivalents of those parameters to calculate our option values. We therefore follow Cox et al. (1985), Bates (1996) and Pan (2002), and transform the $\mathbb{P}$-measured values into their $\mathbb{Q}$-equivalents using the change of measure relations described in those papers. Accordingly, we set $\sigma_V^{\mathbb{Q}} = \sigma_V^{\mathbb{P}}$, $\rho^{\mathbb{Q}} = \rho^{\mathbb{P}}$ and $\kappa^{\mathbb{Q}} = \kappa^{\mathbb{P}} + \gamma(\sigma_V^{\mathbb{P}})^2$, for instance, where γ is a variance risk premium parameter. We choose $\gamma = -4$ in accordance with Ang et al. (2006).

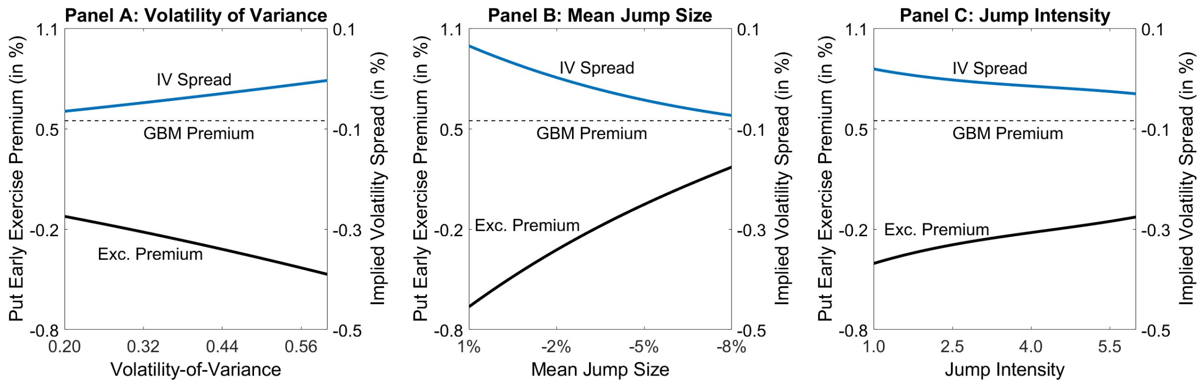

Figure 1: Early Exercise Premiums and IV Spreads Across Parameters The figure plots GBM-world put early exercise premiums (dashed black), plus SV (in Panel A) or SVJ-world (in Panels B and C) excess premiums (solid black) and IV spreads (solid blue) across σ_V, μ_S and λ parameters. In each panel, we put parameter values on the x-axis, while set the premiums on the first (left) and IV spreads on the second (right) y-axes. We describe basecase values of the parameters in Section 2.1.

The figure first point that the early exercise premium of a put under the SV or SVJ world is usually lower than that premium under the equivalent GBM world. This is because put becomes more valuable during the high-marginal utility state, state when the underlying asset value is low, stochastic volatility tends to be high and downward jumps are more likely to occur. Hence, with a low initial asset volatility level, both SV and jumps shift the optimal put early exercise boundary below the equivalent GBM boundary (see, e.g., Amin (1993) and Medvedev and Scaillet (2010)), making American put holders to early exercise less in a SV or SVJ world, and thus pay a lower premium, compared to the equivalent GBM world. Therefore, with a low initial volatility, we would, in general, expect a negative excess premium of the put in the SV and SVJ worlds.

Furthermore, excess premiums and IV spreads are always negatively related, confirming the finding in Campbell et al. (2023), but under a more general setting than their three-period binomial world with time-varying volatility. Although, both SV and jumps have impacts on the magnitudes of the excess premium and IV spread, the impacts, however, are the opposite. A higher level of SV decreases (increases) the size of the excess premium (IV spread), whereas higher asset-value jumps increase (decrease) the size of that premium (IV spread). For a 30-day

ATM put with 20% underlying-asset volatility, the excess premium, for instance, decreases from -0.07% to -0.42% as we move from 20% to 60% σ_V level (see, Panel A), while that same premium increases from -0.61% to 0.22% as we increase μ_S (in absolute term) from 1% to -8% (see, Panel B). Hence, for a plausible range of parameter values, the effect of jumps on excess premiums seems to be significantly more pronounced than the effect of SV (0.59% Vs. 0.35%, in this case, both in absolute terms). The pattern holds even if we look at their impacts on IV spreads (0.15% Vs. 0.07%).

How do we explain the opposing patterns for excess premiums in the presence of SV and jumps? With the SV, a higher volatility shifts the early exercise boundary further downward, lowering the premium with the volatility. With jumps, however, although the boundary is lower, due to the martingale restriction, asset value drift now needs to be higher compared to an equivalent GBM drift, indicating that in a world with jumps, asset value would recover faster after a downward jump compared to the GBM world. This makes jumps rare but desirable events for American put holders as they can now early exercise at a lower asset value, induced by the jump, before that value recovers. And, as the jump magnitude becomes higher, higher is the drift adjustment and asset value recovery speed, making put holders even more willing to early exercise at the jump-induced lower value, and thus pay a higher premium.

With jumps, a key question still remains: how do excess premiums and IV spreads behave with different jump dynamics? As Dierkes et al. (2023) point, asset-value jumps can have varying implications depending on the sources of left-tail variation. Accordingly, in our simulation exercise, although jumps are, in general, related to excess premiums and IV spreads, both the premium and the spread show more drastic change with mean jump-size μ_S, than jump-intensity λ, highlighting that the former has more pronounced impact on premiums and spreads. For instance, while the change in excess premiums for a low-to-high μ_S is 0.59%, that change is only 0.28% for a low-to-high λ (compare Panels B and C).

In the internet appendix, we further explore the dynamics of the excess premium and the

IV spread. For instance, in Section IA.1, we show that the patterns of the premium and the spread with the SV and jumps still remain even if we look for a different moneyness options, or the options has a longer time-to-maturity, or its underlying has a higher volatility.

The fact that σ_V, μ_S and λ can induce early exercise premiums and IV spreads has important implications. Both σ_V and asset-value jumps show negative predictability in the stock return literature (see, Yan (2011) and Baltussen et al. (2018), for instance). Our simulation evidence suggests that excess premium (IV spread) is positively (negatively) related with jumps, while negatively (positively), albeit weakly, related with σ_V. Hence, if we document return predictability for excess premiums (IV spreads) and if that predictability is driven by the SV, we would expect a positive (negative) relationship between excess premiums (IV spreads) and future stock returns. In contrast, if that same predictability is driven by jumps, excess premiums (IV spreads) should be negatively (positively) related with future returns. Recent literature, nevertheless, shows a positive return predictability for IV spreads (see, Cremers and Weinbaum (2010), An et al. (2014), for instance), hinting that any predictability for excess premiums might be negative, and jumps could be the main driver for both of these predictability. We explore this in greater details in the empirical section.

3 Data and Empirical Methodology

In this section, we describe our data sources and filters, and discuss how we calculate the early exercise premiums of a put and the IV spread of an equivalent American option pair, both at the option and the stock level.

3.1 Data Sources and Filters

We obtain daily data from the beginning of January 1996 until the end of April 2016 on American options written on zero-dividend stocks, on the stocks underlying the options, and on the term structure of the risk-free rate from the OptionMetrics IvyDB database. We also extract implied volatilities for our option sample from this database. Market data on the underlying stocks comes from CRSP, firm fundamental data comes from Compustat, and data on the asset pricing factors are from Kenneth French's and Lu Zhang's websites.[9] Finally, data on the daily-cost-to-borrow scores (DCBS), which is a proxy for stock short-sale constraints, comes from the IHS Markit database.

We impose filters on our option data similar to those imposed in the related literature, such as Cremers and Weinbaum (2010). Specifically, we exclude an option pair from the observation month if either the call or put of this pair has zero open interest, missing IV, zero bid price or a price that violates the standard arbitrage bounds (for instance, an American call must lie in-between the maximum of zero and equivalent long forward, and the stock price) at the start of the return generation month. We also exclude observations where start-of-month time value of the put falls below $1 to avoid any market micro-structure issues. Our final sample consists of options with the strike-to-stock price ratio ("Moneyness") of in-between 0.90 and 1.10, and with time-to-maturity starting from two weeks up-until three months.

We include a list of all stock and option based explanatory variables used in our study and their definitions in Table A.1 of the Appendix with our main paper.

3.2 Decomposition of the Early Exercise Premium

To decompose the total put early exercise premium ("Total Premium") into its components, we first recall that the total premium for an exchange-traded American put is the difference between the market price of that put and its equivalent European price:

$$EEP_{i,j}^{total} = P_{i,j}^{A,mkt} - P_{i,j}^{E,mkt}, \tag{3}$$

[9] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and https://global-q.org/index.html. We are grateful to Kenneth French and Lu Zhang for making the data available.

where $EEP_{i,j}^{total}$ and $P_{i,j}^{A,mkt}$ are respectively the total premium and the market price of an exchange-traded American put i written on stock j with strike price K and time-to-maturity T; $P_{i,j}^{E,mkt}$ the market price of the European put written on the same stock with the same strike price and time-to-maturity.

By simultaneously adding and subtracting the equivalent GBM-world theoretical American put price, we can rewrite the Equation (3) as follows:

$$EEP_{i,j}^{total} = \left(P_{i,j}^{A,mkt} - P_{i,j}^{A,GBM}\right) + \left(P_{i,j}^{A,GBM} - P_{i,j}^{E,mkt}\right), \tag{4}$$

where $P_{i,j}^{A,GBM}$ is the GBM-world price of the American put i written on stock j with strike price K and time-to-maturity T. The first part of the Equation (4) shows the excess element of put's total premium not explained under the GBM world ("Excess Premium"), while the second part constitutes its GBM-world premium ("GBM Premium").

3.3 Calculating the Premiums and the IV Spread

As pointed out in Equation (4), we require the GBM-world theoretical American put price to single out the excess premium. We follow the OptionMetrics and calculate this theoretical price using the CRR-based binomial option pricing model and assuming a discretized GBM world. In the CRR framework, underlying asset price can move 'up' or 'down' at each discrete sub-interval $(t, t+1)$ over a total number of periods N within option's time-to-maturity T. The asset value at the end of $t+1$ can be one of the following:

$$S_{j,t+1}(u) = S_{j,t} \times exp\left(\sigma_j\sqrt{\frac{T}{N}}\right), \tag{5}$$

$$S_{j,t+1}(d) = S_{j,t} \times exp\left(-\sigma_j\sqrt{\frac{T}{N}}\right), \tag{6}$$

where $S_{j,t+1}(u)$ and $S_{j,t+1}(d)$ are, respectively, the up and down values of the underlying asset j at the end of the sub-interval $(t, t+1)$; $S_{j,t}$ the asset value at the start of the sub-interval; and σ_j the constant underlying-asset volatility.

To calculate the price of the American put at the initial time, we first set the expiration-day price of the put same as its maturity payoff, $max\left(K - S_{j,T}, 0\right)$. Then, starting from that expiration day, we recursively set the put price at the start of each sub-interval as either the put early exercise payoff at that point (if there is early exercise), or the discounted, risk-neutral probability-weighted value calculated from the end-of-subinterval put prices from the 'up' and 'down' state (if there is no such exercise):

$$P_{i,j,t}^{A,GBM} = \begin{cases} \left[\pi^{\mathbb{Q}} P_{i,j,t+1}^{A,GBM}(u) + (1-\pi^{\mathbb{Q}}) P_{i,j,t+1}^{A,GBM}(d)\right] exp\left(-r_f \sqrt{\dfrac{T}{N}}\right), \text{or} \\ K - S_{j,t}, \end{cases} \tag{7}$$

until we reach at $t = 0$. Here, $\pi^{\mathbb{Q}}$ is the risk-neutral probability of the 'up' state; $P_{i,j,t+1}^{A,GBM}(u)$ and $P_{i,j,t+1}^{A,GBM}(d)$ are American put prices at the 'up' and 'down' state, respectively; and r_f is the risk-free rate.

We calculate the theoretical American price for each sampled put observation using the exact same strike price, time-to-maturity and underlying-stock volatility estimates as in our empirical data for that put and employing $N = 5000$.[10] To estimate the stock volatility, we take the standard deviation from stock's daily return data over a twelve-month rolling period.

Additionally, as shown in Equation (4), we further require exchange-traded equivalent European put prices to calculate the total premium and also the GBM-world premium. However, as exchange-traded single-stock options are exclusively American, there is no market price for equivalent European options. To address this issue, we again rely on Merton's (1973)

[10]OptionMetrics IvyDB US manual highlights that the CRR model becomes exceedingly accurate as the number of time period N goes to 1000. Given that, our choice of $N = 5000$ should give us an accurate representation of the theoretical American put price under the GBM world.

insight that an American call written on a zero-dividend asset is equivalent to a European call. We then *synthetically* create European puts from put-call parity, using a portfolio long the American (i.e. equivalent European) call, long an investment of the discounted strike price in the risk-free asset, and short the underlying stock. We can thus write,

$$P_{i,j}^{synE} = C_{i,j}^{A,mkt} - S_j + Ke^{-r_f T}, \tag{8}$$

where $P_{i,j}^{synE}$ and $C_{i,j}^{A,mkt}$ are, respectively, the prices of synthetic European put and exchange-traded American call, both written on stock j with strike price K and time-to-maturity T.

Armed with the option prices, we next follow Equations (3) and (4) above and calculate different option-level early exercise premiums as,

$$EEP_{i,j}^{total} = P_{i,j}^{A,mkt} - P_{i,j}^{synE}, \tag{9}$$

$$EEP_{i,j}^{excess} = P_{i,j}^{A,mkt} - P_{i,j}^{A,GBM}, \tag{10}$$

$$EEP_{i,j}^{GBM} = P_{i,j}^{A,GBM} - P_{i,j}^{synE}, \tag{11}$$

where $EEP_{i,j}^{excess}$ and $EEP_{i,j}^{GBM}$ are the excess and GBM-world put early exercise premiums, respectively, of an American put i written on stock j with strike price K and maturity T.

Finally, the IV spread for each American option-pair is the difference between the implied volatilities of equivalent American call and put, written on the same underlying stock, with the same strike price and time-to-maturity. We write the option-level IV spread as,

$$IVSprd_{i,j} = IV_{i,j}^{C,A} - IV_{i,j}^{P,A}, \tag{12}$$

where $IVSprd_{i,j}$ is the IV spread for an exchange-traded equivalent American call-put pair i written on stock j with strike price K and time-to-maturity T; $IV_{i,j}^{C,A}$ and $IV_{i,j}^{P,A}$ are, respectively, the implied volatilities of that call and put.

Equipped with option-level IV spreads, we can now calculate the IV spread for a stock. To calculate stock-level spreads, we follow the literature and take a weighted-average of the option-level IV spreads for each stock where weights are calculated as the relative call plus put open interests of the option-pairs:

$$IVSprd_j = \sum_{i=1}^{Z} \left(w_{i,j} \times IVSprd_{i,j} \right), \tag{13}$$

where $IVSprd_j$ is the implied volatility spread for stock j and $w_{i,j}$ the option-pair weights. The weights are calculated as $w_{i,j} = \frac{OI^C_{i,j} + OI^P_{i,j}}{\sum_{i=1}^{Z} OI^C_{i,j} + OI^P_{i,j}}$ where OI is option's open interest and Z the number of option pairs written on a particular stock.

We follow a similar procedure to calculate the stock-level early exercise premiums, although as all three premiums are put based premiums, we weight option-level premiums using the relative open interest of the American put only:

$$EEP^{total}_j = \sum_{i=1}^{Z} \left(w^P_{i,j} \times EEP^{total}_{i,j} \right), \tag{14}$$

$$EEP^{excess}_j = \sum_{i=1}^{Z} \left(w^P_{i,j} \times EEP^{excess}_{i,j} \right), \tag{15}$$

$$EEP^{GBM}_j = \sum_{i=1}^{Z} \left(w^P_{i,j} \times EEP^{GBM}_{i,j} \right), \tag{16}$$

where EEP^{total}_j, EEP^{excess}_j and EEP^{GBM}_j are the weighted-average total, excess and GBM-world premiums for stock j, respectively; and $w^P_{i,j}$ the put weights calculated as $w^P_{i,j} = \frac{OI^P_{i,j}}{\sum_{i=1}^{Z} OI^P_{i,j}}$.

4 Empirical Results

In this section, we present our main empirical evidence on whether the excess put early exercise premium can predict future stock returns, and discuss the source of this predictability. We begin with descriptive statistics of our option-specific variables, calculated at the stock level, and pre-formation characteristics for the stock portfolios sorted on the stock-level excess premium. We then provide the results from various portfolio sorts and Fama and MacBeth (1973) regressions studying the relationship between excess premiums, IV spreads and future stock returns, while controlling for a range of factors and alternative explanations.

4.1 Option Variable Characteristics

Table 1 reports descriptive statistics for excess and GBM-world early exercise premiums and IV spreads (columns (1)-(3)); option moneyness, defined as the ratio of strike-to-underlying-stock price, and days-to-maturity ((4) and (5), respectively); and open interests for calls and puts ((6) and (7), respectively), all calculated at their corresponding stock level. We take observations at the end of each calendar month. We first match option-level observation-pairs for columns (1) to (3) along the moneyness and maturity dimensions so that each pair in one column is associated with exactly one pair in other columns with identical moneyness and maturity. We further match observation-pairs at the stock level so that each equivalent pair in any of these three columns represent the same underlying stock. With the exception of the t-statistic, the descriptive statistics are calculated each sample month and then averaged over time.

TABLE 1 ABOUT HERE

Table 1 first suggests that for an average American put in our sample, the GBM-world early exercise premium is more than double the size of the excess premium. Excess premiums, for instance, are 0.93% (t-statistic: 3.85) of the exchange-traded American put price, on average, compared to the average of 2.06% (t-statistic: 13.70) for GBM-world premiums, suggesting that most part of the typical put early exercise premium comes from GBM-world factors. Importantly however, excess premiums have significantly more variations, as shown by their standard deviation and percentiles. In contrast, GBM premiums only display a negligible volatility. Additionally, while both excess and GBM-world premiums are significantly positive, on average, IV spreads for equivalent American option pairs are significantly negative, in complete agreement with our simulation evidence.

Further looking at the percentiles we observe that, while GBM premiums are only positive, excess premiums in our sample can range from negative to positive. The positive values for GBM premiums highlight that American put prices should always be greater than their equivalent European counterparts under the GBM world, conforming Merton's (1973) insight. In contrast, the varying signs for excess premiums are in line with the jump-based explanation for that premium we establish in our simulation work. We return to this point later.

The moneyness and days-to-maturity statistics, respectively, in columns (4) and (5) suggest that the average option pair for a stock is close to ATM and is less than two months away from the maturity. Additionally, with respect to the open interests for calls and puts, there are disproportions between these two, across different percentiles. Overall, exchange-traded American calls have higher open interests compared to their equivalent put counterparts.

4.2 Preformation Stock Portfolio Characteristics

To begin our empirical analysis, we form stock portfolios by sorting on stock-level excess premiums. At the end of each sample month $t-1$, we sort the universe of stocks in our sample into quintile portfolios according to those premiums. Table 2 reports mean values for different pre-formation characteristics of these portfolios evaluated at or over month $t-1$. The bottom quintile ("Low") contains stocks with low excess premiums, while the top ("High") contains stocks with high premiums. With the exception of the lagged monthly stock return, the numbers in Table 2 are time series averages of the equal-weighted monthly cross-sectional means. For the lagged return, we report both equal-weighted and market value-weighted means.

Table 2 About Here

Table 2 shows that stocks with lower market capitalization and higher book-to-market are located in the "High" portfolio. Consequently, these stocks also have the highest bid-ask spread and Amihud illiquidity measures. Average betas and closing stock prices show little variation, while idiosyncratic volatility remains essentially unchanged across the portfolios. Both equal and value-weighted monthly average lagged returns near-monotonically increase across the portfolios. The equal-weighted returns, for instance, calculated over month $t-1$, increase from 1.21% to 3.51% per month, respectively, from the "Low" to the "High" portfolio.

While showing whether excess premiums can predict future stock returns, we control for these pre-formation characteristics, plus a number of other characteristics, to ensure that our predictability results are not driven by all these features.

4.3 Does The Excess Premium Predict Future Stock Returns?

We next turn our attention to investigating the ability of the excess premium to predict stock returns. To do this, we first conduct univariate portfolio sorts using stock-level excess premiums as follows. At the end of sample month $t-1$, we split the stock universe into quintile portfolios based on the excess premium. The bottom ("Low") quintile contains stocks with low values of the premium, on which the portfolios are formed, while the top ("High") contains stocks with high values of the premium. We also form a "High−Low" spread portfolio that is long the top quintile and short the bottom quintile. We then hold the portfolios over month t and report both equal-weighted (Panel A) and value-weighted returns (Panel B), in excess of the three-month Treasury Bill rate, from the portfolio sort. We further report the monthly average intercept terms (the αs) from regressing the portfolio returns on common risk factors from the market model, the Fama and French (1993)-Carhart (1997) four-factor model (FFC), the Fama and French (2015) five-factor model (FF5), the Hou et al. (2015) q-factor model (HXZq) and the Hou et al. (2021) augmented q-factor model (HMXZq5).[11]

[11] The four factors in the FFC are the market, size and book-to-market factors from Fama and French (1993) and the momentum factor from Carhart (1997), while the FF5 includes the three factors from Fama and French

Table 3 About Here

Table 3 offers the univariate portfolio sort results using excess put early exercise premiums. From the table, we observe that future stock returns decrease as the excess premium increases. Indeed, a strategy that is long the "High" portfolio and short the "Low" portfolio delivers a very significant equal-weighted average monthly excess return of -1.18% (t-statistic: -7.25; see the column labelled "High$-$Low" in Panel A). Additionally, the value-weighted average monthly excess return for that same portfolio is also statistically significant, of -0.70% (t-statistic: -3.87; see the "High$-$Low" column in Panel B).

Risk-adjusted αs for the "High$-$Low" portfolios are also statistically significant regardless of the model we use, and are occasionally higher than the raw returns. For instance, the equal-weighted mean monthly α under the FF5 model is a significant -1.21% (t-statistic: -9.31) for the "High$-$Low" portfolio; the αs are also of similar orders of magnitude for the value-weighted returns. These results therefore suggest that our findings are not due to the failure to adequately control for the usual asset pricing risk factors.

For brevity, we only report the results with the equal-weighting scheme in our subsequent analyses. However, we would like to highlight that all our results still hold under the value-weighting scheme and are qualitatively similar to their equal-weighting counterparts.

Overall, this section offers clear evidence that stock-level excess put premiums can predict underlying stock returns on a monthly horizon. Importantly, the nature of this predictability, i.e. the negative relation between excess premiums and future returns, motivates us to explore the role that jumps could play in this predictability. In our simulation exercise, asset-value jumps are positively linked with excess premiums, while jumps are also negatively priced in future stock returns (see, e.g., Yan (2011) and Dierkes et al. (2023)). Hence, excess premiums predicting stock returns might be due to those premiums capturing the jump dynamics in the

(1993) along with a profitability and an investment factor. In contrast, the HXZq includes the market, size, investment and return-on-equity factors whereas the HMXZq5 extends the HXZq with an expected growth factor.

underlying stock price. We explore this plausibility in the next section.

4.4 The Role of Jumps

While the results in Section 4.3 provide encouraging evidence that excess premiums can predict stock returns, an important question still remains: how do we explain this predictability? Our simulation work hinges toward suggesting that jumps and SV can drive the variation in excess premiums. Hence, to test whether these two fundamental sources of asset-value shocks can explain the predictability in excess premiums, we first undertake two bivariate portfolio sorts, separately using either a jump or a SV measure, and the excess premium as sorting variables. As a proxy for jumps, we use the option-implied ($\mathbb{Q}$-measured) left-tail variation measure ("*JumpLT*") from Bollerslev and Todorov (2011),[12] while we follow Baltussen et al. (2018) in calculating the volatility-of-variance ("VoV") measure which captures the SV effect. At the end of each sample month $t-1$, we first separately split the stock universe into quintile portfolios according to each sorting variable and create $5 \times 5 = 25$ independent but bivariately sorted portfolios. The bottom quintile for each sort contains stocks with low factor values ("Low"), while the top contains stocks with high values ("High"). We also form a spread portfolio long the top and short the bottom quintile ("High−Low") along the excess premium dimension. We then hold the portfolios over month t and calculate returns on these portfolios.

TABLE 4 ABOUT HERE

Table 4 reports our bivariate sort results. In Panel A, we conduct the sort using *JumpLT* and excess premium as sorting variables, while in Panel B, we replace *JumpLT* with VoV. Looking at the results in Panel A, we observe a variable pattern in monthly average stock returns across excess premium-sorted portfolios depending on whether we sort the premiums

[12] As Dierkes et al. (2023) show, *JumpLT* measure (known as $BT11Q$ in Dierkes et al. (2023)) performs the best among its peers in capturing a range of future jump-dynamics, and also future returns.

at lower or higher *JumpLT* levels. Average excess returns on the "High−Low" spread portfolio, for instance, show almost a fivefold increase, from −0.51% (t-statistic: −2.46) to −2.38% (t-statistic: −4.25), respectively from the "Low" to "High" *JumpLT* levels. In contrast, the "High−Low" portfolios sorted at different VoV levels do not show such variation. Average excess return of the spread portfolio, for instance, is −1.14% at the "Low" VoV level, which is similar to the −1.05% return of that same portfolio at the "High" VoV level. Accordingly, our bivariate portfolio sort exercise points that jumps play the main role in explaining the stock return predictability of excess premiums we observe in our sample data.[13]

Although the bivariate portfolio sort establishes a link between ex-ante jumps and the predictability in excess premiums, the jump proxy in that sort is an overall left-tail variation measure, hence can vary with the change in both jump-size μ_S and jump-intensity λ. Importantly however, our simulation evidence suggests that the change in μ_S, rather than λ, mainly drives the excess premium dynamics. To this end, we follow Yan (2011) and Cremers et al. (2015), and calculate a μ_S proxy ("*JumpSize*") from the IV slope, using IVs of 30-day OTM put and ATM call, both taken from the IV surface. Interestingly, excess premiums and *JumpSize* are highly positively correlated, consistent with our simulations, with a mean cross-sectional correlation of around 63%. We next conduct univariate portfolio sort exercise in Table 5 where we independently sort stocks using orthogonalized excess premium variable, disentangled from the effect of *JumpSize* (Panel A). To explore further, we decompose *JumpSize* into its systematic and idiosyncratic parts, separately orthogonalize excess premiums from either of these two, and then conduct another sort exercise (Panel B).

Following Yan (2011), to decompose the *JumpSize* into its systematic and idiosyncratic components, we run a twelve-month rolling window regression as: $JumpSize_{i,t-1} = z_i + \beta_i JumpSize_{S\&P500,t-1} + \epsilon_{i,t-1}$, where $JumpSize_{i,t-1}$ and $JumpSize_{S\&P500,t-1}$ are the mean

[13]Although our theory suggests ex-ante jumps, we further conduct the same bivariate sort (unreported) separately using two realized jump proxies: expected shortfall in Artzner et al. (1999) and $\mathbb{P}$-measured left-tail in Atilgan et al. (2020). The inference from those sorts is exactly the same as the bivariate sort with *JumpLT*.

jump-size proxy measures for stock i and $S\&P500$, respectively, at the end of month $t-1$. Then, the fitted and the residual values from this regression are, respectively, the systematic and idiosyncratic components of $JumpSize$ for each stock. Finally, to orthogonalize a variable from another, we run cross sectional regression for each sample month $t-1$ as: $var_1 = \alpha_1 + \beta_1 var_2 + \epsilon_1$, where var_1 and var_2 are the variables in their original forms, α_1 and β_1 the regression parameters and ϵ_1 the orthogonalized part of var_1, independent from the effect of var_2 on var_1.

At the end of month $t-1$, we separately split stocks into quintile portfolios based on each sorting variable, same as the excess premium sort in Table 3. We also form a "High–Low" spread portfolio for each sort which is long the top and short the bottom quintile. We hold all portfolios over month t and then calculate their returns.

TABLE 5 ABOUT HERE

Panel A of Table 5 first shows that, consistent with the prior literature, future stock returns decrease as the $JumpSize$ increases. Furthermore, although excess premiums are negatively related with future returns, once we control for the impact of $JumpSize$ in excess premiums, that relationship severely weakens. The "High–Low" spread portfolio, sorted on the orthogonalized excess premium and independent from the $JumpSize$, for instance, produces a mean monthly excess return of -0.43% (t-statistic: -1.80). This is significantly lower (in absolute term) than the -1.18% (t-statistic: -7.25) mean return for that same portfolio when sorted on the non-orthogonalized excess premium. Further looking into Panel B, we observe that the predictability of excess premiums is mainly driven by the idiosyncratic component of $JumpSize$, while the systematic component only plays a minor role. Altogether, the results in these two panels provide further evidence that mean jump-size μ_S plays the prominent role in explaining excess premium's return predictability.

In Panel C, we finally evaluate whether excess premiums, and ultimately the presence of jumps, can play any part in explaining the prediction power of IV spreads that prior literature documents. As mentioned earlier, literature is mostly divided on the source of IV spreads' stock return predictability. Studies, for instance, have indicated that the predicability might arise due to the trading activities of informed investors, or IV spreads capturing the temporary mispricing of the underlying stock, or market frictions (see, Cremers and Weinbaum (2010), Goncalves-Pinto et al. (2020) and Hiraki and Skiadopoulos (2023), for instance). Contrary to these, we seek for a jump-based explanation for IV spreads' predictability. Our simulation evidence suggests negative associations between IV spreads and excess premiums, and between IV spreads and μ_S. Indeed, in our sample data, IV spreads are highly negatively correlated with these two, with the mean cross-sectional correlations for the pairs ranging from 79% to 80%. More importantly, once we orthogonalize IV spreads from the impact of excess premiums or $JumpSize$, IV spreads significantly lose the predictive power. The "High–Low" spread portfolio in Table 5, for instance, sorted on non-orthogonalized IV spreads, generates a mean excess return of 1.29% (t-statistic: 7.50), in line with the previous literature. In comparison, when we do the sort based on the orthogonalized IV spread variable, independent from the effect of excess premium, that same spread portfolio only provides a 0.53% (t-statistic: 2.61) mean return. The pattern is also very similar even when we orthogonalize the IV spread from the $JumpSize$, instead of the excess premium.

Taken altogether, the results in this section strongly suggest that jumps, more specifically mean asset-value jump-size μ_S, play an important role in explaining the ability of the excess premium and IV spread to predict stock returns.

4.5 Alternative Hypotheses

We next examine several alternative hypotheses for the predictability of excess premiums and IV spreads. Doing so, we test whether the findings we document in Section 4.4 still prevail under these hypotheses. We first check whether informed trading can explain our results. As Cremers and Weinbaum (2010) point, informed traders, having access to the private information, first trade in the options, ahead of the stock market. Hence, information might appear in options first, and then lead to the stocks. This explains why put-call parity deviations, in the guise of IV spreads, can predict stock returns in Cremers and Weinbaum (2010). As put-call parity deviations can be linked with option early exercises, a natural question to ask is whether the return predictability for excess premiums can also be explained by informed trading.

Following Shang (2017), we create a sub-sample of options only including observations with zero trading volumes, keeping in mind that if informed trading explains our results we should not find the patterns we observe in Table 5 for this sub-sample. We then repeat the analysis in Table 5, but only for our main sorting variables, on this sample. The results from this analysis are presented in Panel A of Table 6.

TABLE 6 ABOUT HERE

Panel A shows that even when the sample solely consists of options with zero trading volume, our previous inferences persist. For instance, the "High–Low" spread portfolio formed from the excess premium sort still produces a mean monthly excess return of −1.17% (t-statistic: −6.13). The IV spread remains positively related with stock returns, conforming with Shang (2017) and Goncalves-Pinto et al. (2020). Furthermore, when we orthogonalize IV spreads from excess premiums and then conduct the IV spread sort, the spread portfolio produces a mean return of only 0.54% (t-statistic: 2.04), significantly lower than the mean return of 1.30% (t-statistic: 5.58) under the non-orthogonalized IV spread sort.

We next test whether mispricing due to stock price pressure can explain our results. Goncalves-Pinto et al. (2020) show that price pressure, driven by interim liquidity shock in the stock, can shift the stock price away from its option-implied value. Hence, price pressure can lead to a deviation in put-call parity relation (thus, might relate to early exercises) for an equivalent option pair written on that stock and can generate IV spread for that pair. Once that temporary shock dissipates, stock price reverts back to its fundamental value. In the mean time, the IV spread (and potentially, early exercises), generated by the short-term mispricing, can display predictability of stock returns. To control for the temporary price pressure effect, we follow Goncalves-Pinto et al. (2020) and skip a day from return generation, that is, we only start cumulating stock returns from the second day after portfolio formation. The reason behind this set-up, as indicated by Goncalves-Pinto et al. (2020), is that if our results are driven by the temporary shock due to price pressure, we should not observe significant returns for our spread portfolios if we skip the first day. We examine this in Panel B.

Looking at the results in Panel B, we note that although the first-day return accounts for a sizable proportion, we still have significant mean returns of -0.64% (t-statistic: -4.12) and 0.69% (t-statistic: 4.30) for spread portfolios, sorted separately on the excess premium and the IV spread, respectively, even when we skip the first day. Importantly, the excess premium (and its embedded jump effect) yet explains a significant part of IV spreads' return predictability. Orthogonalizing from the excess premium, IV spread sort, for instance, only generates a marginally significant mean return of 0.37% (t-statistic: 1.88) for the spread portfolio.[14]

We finally investigate whether our results are due to frictions in the stock market. Hiraki and Skiadopoulos (2023) show that IV spreads can change in the presence of transaction costs of the underlying stock. As investors demand compensation for their exposure to frictions, this could ultimately lead to IV spreads predicting stock returns. Similarly, Jensen and Pedersen (2016) and Figlewski (2022) show that investors can change their optimal early exercise decisions in the presence of stock short selling constraints and/or transaction costs. To test this friction-based channel, we create sub-samples based on either scaled bid-ask spreads of the stock (Panel C) or stock DCBS (Panel D). While bid-ask spreads work as a proxy for stock liquidity, DCBS highlight short sale constraints of the stock. As Jensen and Pedersen (2016) point, stocks with DCBS greater than five are hard-to-short stocks. Using bid-ask spreads, we first create two stock sub-samples: one where bid-ask spreads are lower than the median

[14] In an alternative test, we further check whether our results survive controlling for a longer-term mispricing proxy from Stambaugh et al. (2015). The results, in that case, are in complete agreement with Panel B results.

spread (“Liquid Stocks”), and the other with spreads higher than the median spread (“Illiquid Stocks”). We further create two sub-samples based on DCBS. In one, we include all stocks with available DCBS and in other, we exclude stocks with DCBS greater than five. We next conduct the portfolio sort exercise using each sub-sample and report their results.

The results in Panels C and D highlight that although return predictabilities of the excess premium and the IV spread are stronger with comparatively illiquid and hard-to-short stocks, we still have significant predictive ability for the liquid and easy-to-short stocks. In the liquid stock sample, for instance, the “High–Low” portfolios sorted on the excess premium and the IV spread respectively generate mean excess returns of −0.70% (*t*-statistic: −4.04) and 0.80% (*t*-statistic: 4.68) (see Panel C1). Once again, if we orthogonalize the IV spread from excess premium and then conduct the sort with the orthogonalized IV spread, the spread portfolio becomes insignificant, with a mean return of only 0.03% (*t*-statistic: 0.13).

4.6 Fama-MacBeth (FM; 1973) Regressions

We further run FM regressions to see whether a number of commonly used cross-sectional stock-related factors can explain the apparent return predictability we document in Tables 3 and 5. In particular, we control for stock characteristics such as firm size, the book-to-market ratio, stock’s beta, its idiosyncratic volatility, momentum, reversal, bid-ask spread and Amihud (2002) illiquidity measure of the stock. We also control for the price pressure and friction proxies, respectively, from Goncalves-Pinto et al. (2020) and Hiraki and Skiadopoulos (2023). As these proxies are highly correlated with the IV spread, and hence with the excess premium, we orthogonalize them and only include the orthogonalized parts in our regressions. We finally control for the *JumpSize* and VoV measures to observe the impact of these two in the regressions. In Table 7, we first present mean cross-sectional correlations for all variable pairs used in the regressions. We then report the regression results in Table 8.

Table 7 About Here

Table 8 About Here

FM regressions further confirm our earlier portfolio-sort findings. For instance, even after controlling for various stock characteristics, while excluding the *JumpSize*, the relationship between the excess premium and stock returns remains negative and significant. Once we include the *JumpSize* in the regression, that relationship, nevertheless, disappears. Taken altogether, the results in this section strongly suggest that excess premiums can significantly predict stock returns and such predictability is primarily driven by their ability to capture mean jump-size in the underlying stock. Other factors only have secondary effect on that predictability.

We also conduct a number of robustness tests in Sections IA.4 − IA.7 of our internet appendix. More specifically, we check whether our results survive when we group options into various moneyness and maturity categories, whether our findings are due to the choice of calculating the GBM-world American put price under CRR method, whether an alternative definition of the stock-level excess premium can impede the findings, whether our results are due to separate closing times for stock and option markets,[15] whether the results survive in a sample created from liquid-only options with positive trade volumes, plus a number of further checks. Our empirical results still remain intact even after all these supplementary tests.

5 Concluding Remarks

We investigate whether option early exercises contain significant information about future underlying stock price movements. More specifically, we show that the early exercise premium

[15] The options market closes two minutes after the stock market.

of single-stock American put, in excess of its equivalent GBM-world premium, can negatively predict both value and equal-weighted cross-sectional future stock returns. Looking for the source of this predictability, our simulation evidence first suggests a positive relationship between asset-value jumps, especially, mean jump-size and excess premium of a put. Further evidence negatively relates jump-size with the IV spread of an equivalent American option pair, implying a negative association between the excess premium and IV spread, induced by jumps. Prior literature shows that mean jump-size is negatively priced in future stock returns (see, e.g., Yan (2011)). Hence, based on our simulations, we make a conjecture that jumps might help us to understand the negative (positive) relationship between excess premium (IV spread) and future returns that we document in this paper (previous literature, such as Cremers and Weinbaum (2010), documents). Using a barrage of empirical tests and robustness checks, we show that jumps indeed play the key role in explaining both predictability.

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Table 1: Descriptive Statistics for the Option Variables

The table presents descriptive statistics on the month-end spreads between exchange-traded American puts and their equivalent GBM-world theoretical American puts under the CRR scheme ("Excess Premium"; column (1)), between theoretical American puts and equivalent synthetic European puts ("GBM Premium"; (2)), and between equivalent Black-Scholes based American call and put implied volatilities ("IV Spread"; (3)), all calculated at the stock level from corresponding single-stock options using option open-interest weights. Both premiums are scaled by the traded American put price. The table further reports the stock-level average moneyness ((4)) and time-to-maturity ((5)), calculated from their corresponding option-level statistics, along with the stock-level average open interests, measured as the average number of option contracts outstanding, separately for American calls and puts written on the stock ((6) and (7), respectively). The descriptive statistics include the mean, the standard deviation (StDev), the t-statistic of the mean (Mean/StdErr), several percentiles, and the number of observations at the stock and option levels (Obs (Stocks) and Obs (Options), respectively). The observation-pairs used in columns (1)-(3) are matched, so that each pair corresponds to the same underlying stock. At the option level, we calculate moneyness as the ratio of option strike-to-stock price and measure time-to-maturity in calendar days. With the exception of the t-statistic, each statistic is calculated as the time-series average of respective cross-sectional statistics.

	Excess Premium (in %)	GBM Premium (in %)	IV Spread (in %)	Money-ness (K/S)	Maturity Time (in days)	Open Interest (Call)	Open Interest (Put)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean	0.93	2.06	−1.47	1.00	50	1,111	831
StdDev	10.71	1.31	6.15	0.03	18	3,002	2,903
Mean/StdErr	[3.85]	[13.70]	[−11.48]				
Percentile 1	−26.55	0.82	−23.39	0.92	19	3	2
Percentile 5	−12.88	0.99	−9.63	0.95	20	14	8
Quartile 1	−3.69	1.35	−2.55	0.98	39	89	49
Median	0.16	1.79	−0.64	1.00	49	306	181
Quartile 3	4.63	2.52	0.80	1.01	60	951	630
Percentile 95	17.64	3.93	4.35	1.05	80	4,503	3,272
Percentile 99	36.25	6.03	9.78	1.08	80	13,306	10,329
Obs (Stocks)	932	932	932	932	932	932	932
Obs (Options)	3,814	3,814	3,814	3,814	3,814	3,814	3,814

Table 2: Average Preformation Characteristics of Portfolios Sorted on the Excess Put Early Exercise Premium

The table presents preformation characteristics of the stock portfolios sorted on the stock-level excess put early exercise premium ("Excess Premium"). See the caption of Table 1 for the definition of excess premium. At the end of each sample month t, we first sort stocks into portfolios according to the quintile breakpoints of the excess premium. We then calculate relevant stock-related characteristics for the stocks within each portfolio based on information available at time t and report their portfolio averages. The stock characteristics include: market capitalization of the stocks (Market Size); their book-value-to-market-size ratio (B/M); their beta, calculated over the prior 60 months from the market model (CAPM Beta); both equal and value-weighted portfolio returns over month $t-1$ to t (Lag Monthly Returns); stock idiosyncratic volatility, calculated as the standard deviation of the residuals from Fama-French (1993)-Carhart (1997) regression model (FFC) estimated over the prior year; closing price of the stocks; their bid-ask spreads, measured as the percentage of the closing price; and Amihud (2002) stock illiquidity measure, calculated as the absolute stock return divided by its dollar volume.

	1 (Low)	2	3	4	5 (High)
Market Size (in $MN)	8,755	9,409	8,866	7,651	4,995
B/M	0.94	0.78	0.83	0.98	1.16
CAPM Beta	1.25	1.32	1.33	1.29	1.19
Lag Monthly Return (in %, EW)	1.21	1.04	1.26	1.94	3.51
Lag Monthly Return (in %, VW)	1.37	1.13	1.40	1.93	3.32
Stock Idiosyncratic Volatility	0.37	0.38	0.38	0.38	0.37
Closing Price	53.55	45.13	42.90	43.24	45.28
Bid-Ask Spread (in %)	0.43	0.35	0.36	0.41	0.51
Amihud (in multiple of 10,000)	0.37	0.28	0.29	0.35	0.52

Table 3: Excess Returns and Alphas from Excess Premium-Sorted Portfolios

The table presents the equal-weighted (Panel A) and market-value weighted (Panel B) mean returns and risk-adjusted αs of the stock portfolios (both in %), in excess of the three-month Treasury Bill rate, univariately sorted on the stock-level excess put early exercise premium ("Excess Premium"). See the caption of Table 1 for the definition of excess premium. We calculate αs as the intercept estimated from: the market model (MKT), where portfolio excess returns are regressed on the market factor; the Fama-French (1993)-Carhart (1997) four-factor model (FFC), where excess returns are regressed on the market, size, book-to-market and momentum factors; the Fama and French (2015) five-factor model (FF5), where excess returns are regressed on the market, size, book-to-market, profitability and investment factors; the Hou et al. (2015) q-factor model (HXZq), where excess returns are regressed on the market, size, investment and return-on-equity factors; and the Hou et al. (2021) augmented q-factor model (HMXZq5), where excess returns are regressed on the HXZq factors, plus the expected growth factor. At the end of month $t-1$, we sort stocks into portfolios according to the quintile breakpoints of the excess premium. We also form a spread portfolio long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. Observations in both panels are matched, so that all correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics, calculated using a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
			Panel A: Equal-Weighted Evidence			
Excess Return	0.91	0.67	0.46	0.25	−0.27	−1.18
	[2.17]	[1.50]	[1.02]	[0.58]	[−0.67]	[−7.25]
α_{MKT}	0.15	−0.12	−0.33	−0.50	−0.95	−1.11
	[0.80]	[−0.57]	[−1.69]	[−2.84]	[−5.60]	[−8.38]
α_{FFC}	0.22	−0.03	−0.28	−0.46	−0.95	−1.17
	[1.89]	[−0.22]	[−2.50]	[−4.07]	[−8.51]	[−9.35]
α_{FF5}	0.38	0.22	−0.10	−0.30	−0.84	−1.21
	[3.24]	[1.96]	[−0.94]	[−2.69]	[−7.38]	[−9.31]
α_{HXZq}	0.95	0.71	0.56	0.30	−0.32	−1.28
	[2.07]	[1.47]	[1.17]	[0.67]	[−0.79]	[−8.90]
α_{HMXZq5}	0.90	0.71	0.53	0.32	−0.34	−1.24
	[1.85]	[1.38]	[1.03]	[0.66]	[−0.77]	[−8.15]
			Panel B: Value-Weighted Evidence			
Excess Return	0.82	0.66	0.47	0.41	0.13	−0.70
	[2.09]	[1.61]	[1.15]	[1.04]	[0.32]	[−3.87]
α_{MKT}	0.19	0.00	−0.21	−0.21	−0.46	−0.65
	[1.40]	[0.01]	[−1.72]	[−1.96]	[−3.94]	[−3.59]
α_{FFC}	0.28	0.08	−0.17	−0.24	−0.51	−0.79
	[2.21]	[0.64]	[−1.54]	[−2.20]	[−4.34]	[−4.62]
α_{FF5}	0.35	0.24	−0.02	−0.20	−0.48	−0.83
	[2.62]	[1.98]	[−0.21]	[−1.79]	[−3.94]	[−4.63]
α_{HXZq}	0.81	0.71	0.53	0.43	0.06	−0.75
	[2.16]	[1.85]	[1.35]	[1.22]	[0.17]	[−3.95]
α_{HMXZq5}	0.84	0.84	0.56	0.43	0.11	−0.73
	[2.11]	[2.06]	[1.36]	[1.14]	[0.31]	[−3.60]

Table 4: Independent Double Portfolio Sort Exercise

The table presents the mean percentage returns of equal-weighted stock portfolios, in excess of the three-month Treasury Bill rate, double-sorted on the excess put early exercise premium ("Excess Premium") and either a left-tail variation measure ("*JumpLT*"; Panel A) or the volatility-of-variance ("VoV"; Panel B), all measured at the stock level. See the caption of Table 1 for the definition of excess premium. While we use OTM put prices to compute the *JumpLT*, based on Bollerslev and Todorov (2011), we calculate the VoV from option implied volatilities, following Baltussen et al. (2018). At the end of each sample month $t-1$, we first separately sort stocks into portfolios according to the quintile breakpoints of excess premium and *JumpLT* (VoV), and then create 5×5 = 25 independently double-sorted portfolios. We also form spread portfolios long the top and short the bottom quintile ("High−Low") along the excess premium dimension and hold all portfolios over month t. Observations on the sorting variables are matched, so that they correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

Panel A: Sort Variables - Excess Premium and *JumpLT*

	Excess Premium					
JumpLT	1 (Low)	2	3	4	5 (High)	High–Low
1 (Low)	1.14	0.96	0.69	0.50	0.63	−0.51
	[3.61]	[3.13]	[2.15]	[1.59]	[1.65]	[−2.46]
2	1.01	1.15	0.74	0.39	0.34	−0.67
	[2.50]	[2.73]	[1.90]	[1.03]	[0.83]	[−2.08]
3	0.77	0.92	0.56	0.42	0.16	−0.61
	[1.53]	[1.83]	[1.11]	[0.81]	[0.33]	[−2.30]
4	0.40	0.50	0.55	0.48	−0.09	−0.49
	[0.71]	[0.76]	[0.88]	[0.80]	[−0.17]	[−1.70]
5 (High)	0.65	−0.37	−0.53	−0.87	−1.74	−2.38
	[0.83]	[−0.48]	[−0.66]	[−1.23]	[−2.63]	[−4.25]

Panel B: Sort Variables - Excess Premium and VoV

	Excess Premium					
VoV	1 (Low)	2	3	4	5 (High)	High–Low
1 (Low)	1.00	0.86	0.82	0.41	−0.14	−1.14
	[2.23]	[2.03]	[1.98]	[0.98]	[−0.28]	[−4.14]
2	1.02	0.96	0.51	0.22	−0.15	−1.17
	[2.42]	[2.12]	[1.10]	[0.52]	[−0.35]	[−5.51]
3	0.88	0.67	0.38	0.50	−0.31	−1.18
	[2.12]	[1.49]	[0.75]	[1.07]	[−0.76]	[−7.66]
4	0.99	0.45	0.21	0.22	−0.27	−1.26
	[2.19]	[0.92]	[0.44]	[0.49]	[−0.59]	[−4.36]
5 (High)	0.67	0.46	0.17	−0.31	−0.38	−1.05
	[1.43]	[0.92]	[0.31]	[−0.60]	[−0.91]	[−3.60]

Table 5: Univariate Portfolio Sort Exercise

The table presents the excess mean percentage returns of equal-weighted stock portfolios, univariately sorted on a mean jump-size proxy ("*JumpSize*") from Yan (2011) and left-tail variation measure ("*JumpLT*") from Bollerslev and Todorov (2011), on systematic ("$JumpSize_{sys}$") and idiosyncratic ("$JumpSize_{idio}$") components of the *JumpSize*, on excess put early exercise premium ("Excess Premium") and implied volatility spread ("IV Spread"), and on several orthogonalized variables. In Panels A and B, we check the jump-based explanation for excess premiums, while in Panel C, we test that same explanation for IV spreads. See the caption of Table 1 for the definitions of excess premium and IV spread. We denote the orthogonalized variables with an ε superscript and include the variable they are orthogonalized from in their parentheses. At the end of month $t-1$, we separately sort stocks into portfolios according to the quintile breakpoints of each sorting variable. We also form a spread portfolio long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. Observations on the sorting variables are matched, so that all correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: Jumps and Excess Premiums						
JumpSize	0.86	0.70	0.55	0.21	−0.30	−1.16
	[2.21]	[1.81]	[1.33]	[0.47]	[−0.59]	[−5.40]
JumpLT	0.79	0.73	0.56	0.36	−0.69	−1.48
	[2.54]	[1.96]	[1.18]	[0.64]	[−1.00]	[−2.72]
Excess Premium	0.91	0.67	0.46	0.25	−0.27	−1.18
	[2.17]	[1.50]	[1.02]	[0.58]	[−0.67]	[−7.25]
Excess Premium$^{\varepsilon}$(*JumpSize*)	0.47	0.58	0.54	0.39	0.04	−0.43
	[0.93]	[1.23]	[1.24]	[0.98]	[0.12]	[−1.80]
Excess Premium$^{\varepsilon}$(*JumpLT*)	0.72	0.66	0.47	0.25	−0.20	−0.92
	[1.65]	[1.42]	[1.03]	[0.57]	[−0.50]	[−5.01]
Panel B: Systematic Vs. Idiosyncratic Jump-Size and Excess Premiums						
$JumpSize_{sys}$	0.61	0.74	0.62	0.46	0.14	−0.48
	[1.54]	[1.95]	[1.54]	[1.01]	[0.26]	[−2.06]
$JumpSize_{idio}$	0.92	0.76	0.67	0.41	−0.20	−1.12
	[2.16]	[1.87]	[1.61]	[0.99]	[−0.40]	[−5.62]
Excess Premium$^{\varepsilon}$($JumpSize_{sys}$)	0.86	0.87	0.55	0.42	−0.13	−0.99
	[2.01]	[1.82]	[1.24]	[1.02]	[−0.31]	[−5.71]
Excess Premium$^{\varepsilon}$($JumpSize_{idio}$)	0.66	0.74	0.50	0.50	0.16	−0.50
	[1.41]	[1.62]	[1.19]	[1.19]	[0.42]	[−2.46]
Panel C: Jumps and IV Spreads						
IV Spread	−0.46	0.22	0.63	0.78	0.84	1.29
	[−0.99]	[0.51]	[1.54]	[1.90]	[1.95]	[7.50]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.04	0.39	0.52	0.66	0.49	0.53
	[−0.09]	[0.82]	[1.27]	[1.72]	[1.29]	[2.61]
IV Spread$^{\varepsilon}$ (*JumpSize*)	−0.05	0.33	0.64	0.59	0.51	0.56
	[−0.13]	[0.84]	[1.65]	[1.34]	[0.96]	[2.67]

Table 6: Alternative Hypotheses for Excess Premium and IV Spread Predictability
The table presents the mean excess percentage returns of equal-weighted stock portfolios, univariately sorted on the excess premium, the IV spread and an orthogonalized IV spread variable, all measured at the stock level. See the caption of Table 1 for the definitions of excess premium and IV spread. We denote the orthogonalized variables with an ε superscript and include the variable they are orthogonalized from in their parentheses. At the end of month $t-1$, we sort stocks into portfolios according to the quintile breakpoints of each of the three sorting variables. We also form a spread portfolio long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. We first conduct the sort exercise using variables exclusively formed from zero trading volume observations for both calls and puts (Panel A). We next return to our standard definition and calculate the sorting variables from all option observations. We then use these variables to form stock portfolios, but only start generating returns from the second day after portfolio formation (Panel B). We further conduct portfolio sorts for sub-samples based on whether the underlying stock is liquid or illiquid (Panel C), and for sub-samples formed on stock short sale constraints (Panel D). We calculate stock liquidity from stock bid-ask spreads, scaled by the closing price, while we use stock Daily-Cost-to-Borrow Scores (DCBS) to proxy for its short sale constraints. The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: Sample With Only Zero Option Trade Volume Observations						
Excess Premium	0.96	0.94	0.46	0.43	−0.21	−1.17
	[2.28]	[2.03]	[0.97]	[0.98]	[−0.53]	[−6.13]
IV Spread	−0.33	0.37	0.68	0.87	0.97	1.30
	[−0.71]	[0.80]	[1.63]	[1.97]	[2.31]	[5.58]
IV Spread$^{\varepsilon}$(Excess Premium)	0.10	0.33	0.74	0.76	0.64	0.54
	[0.19]	[0.73]	[1.71]	[1.88]	[1.62]	[2.04]
Panel B: Excluding First Day Returns						
Excess Premium	0.53	0.47	0.36	0.27	−0.11	−0.64
	[1.39]	[1.17]	[0.90]	[0.71]	[−0.31]	[−4.12]
IV Spread	−0.24	0.21	0.51	0.58	0.45	0.69
	[−0.60]	[0.54]	[1.43]	[1.59]	[1.13]	[4.30]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.01	0.29	0.37	0.51	0.36	0.37
	[−0.03]	[0.70]	[1.04]	[1.50]	[1.02]	[1.88]
Panel C: Conditioning on the Stock Liquidity						
Panel C1: Liquid Stocks						
Excess Premium	0.91	0.87	0.52	0.44	0.21	−0.70
	[1.97]	[1.70]	[1.00]	[0.93]	[0.48]	[−4.04]
IV Spread	0.09	0.53	0.61	0.83	0.89	0.80
	[0.17]	[1.05]	[1.32]	[1.76]	[1.95]	[4.68]
IV Spread$^{\varepsilon}$(Excess Premium)	0.51	0.61	0.60	0.71	0.54	0.03
	[0.87]	[1.10]	[1.26]	[1.70]	[1.38]	[0.13]
Panel C2: Illiquid Stocks						
Excess Premium	0.91	0.43	0.35	−0.08	−0.63	−1.53
	[2.33]	[0.99]	[0.86]	[−0.18]	[−1.51]	[−7.00]
IV Spread	−0.88	−0.04	0.44	0.56	0.89	1.76
	[−1.93]	[−0.09]	[1.13]	[1.43]	[2.10]	[7.09]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.54	0.16	0.42	0.48	0.46	1.00
	[−1.17]	[0.37]	[1.07]	[1.25]	[1.17]	[4.08]

(continued on next page)

Table 6: Alternative Hypotheses for Excess Premium and IV Spread Predictability (Cont.)

	1 (Low)	2	3	4	5 (High)	High−Low
Panel D: Conditioning on Stock Short Sale Constraints						
Panel D1: With All Available DCBS						
Excess Premium	0.81	0.73	0.66	0.55	−0.06	−0.87
	[1.72]	[1.50]	[1.44]	[1.13]	[−0.12]	[−6.95]
IV Spread	−0.07	0.48	0.70	0.74	0.83	0.90
	[−0.12]	[1.02]	[1.58]	[1.56]	[1.76]	[6.06]
IV Spread$^{\varepsilon}$(Excess Premium)	0.20	0.58	0.60	0.73	0.60	0.41
	[0.37]	[1.13]	[1.24]	[1.58]	[1.36]	[2.03]
Panel D2: Excluding Stocks with DCBS > 5						
Excess Premium	0.82	0.73	0.64	0.63	0.21	−0.61
	[1.74]	[1.50]	[1.38]	[1.31]	[0.42]	[−5.36]
IV Spread	0.16	0.58	0.70	0.73	0.85	0.69
	[0.30]	[1.26]	[1.61]	[1.53]	[1.78]	[5.01]
IV Spread$^{\varepsilon}$(Excess Premium)	0.46	0.61	0.58	0.76	0.62	0.16
	[0.90]	[1.19]	[1.21]	[1.66]	[1.39]	[0.88]

Table 7: Pair-wise Correlations of the Study Variables

The table presents the mean cross-sectional correlation coefficients for all the variable pairs in our study. At the end of each month $t-1$, we calculate Pearson correlation for each pair from their cross-sectional stock-level observations and report the time-series mean in the table. The variable list includes our key variables - the excess premium (ExPrem) and the IV spread, plus a range of other explanatory variables - such as a mean jump-size ($JSize$) proxy from Yan (2011); a left-tail variation measure (JLT) from Bollerslev and Todorov (2011); volatility-of-variance (VoV) from Baltussen et al. (2018); a stock price pressure measure (DOTS) from Goncalves-Pinto et al. (2020); and a stock friction measure (CFER) from Hiraki and Skiadopoulos (2023). We also include a number of common control variables such as size, as measured by the natural logarithm of the market value of the stock; the book-to-market ratio (BM); the beta of the stock, estimated over the prior 60 months from the market model; idiosyncratic volatility (IdioVol), calculated from the standard deviation of the residuals from the Fama-French (1993)-Carhart (1997) regression model estimated over the prior 60 months; momentum, measured as the cumulative stock return over months $t-12$ to $t-1$; reversal, measured as the stock return over months $t-2$ to $t-1$; bid-ask spread of the stock, computed as the percentage of the stock price; and the Amihud (2002) stock illiquidity measure, calculated as the absolute stock return divided by stock dollar volume.

	ExPrem	IVSpread	$JSize$	JLT	VoV	DOTS	CFER	Size	BM	Beta	IdioVol	Momentum	Reversal	BidAsk	Amihud
ExPrem	1.00														
IVSpread	−0.80	1.00													
$JSize$	0.63	−0.79	1.00												
JLT	0.12	−0.25	0.31	1.00											
VoV	0.12	−0.19	0.15	0.00	1.00										
DOTS	−0.75	0.94	−0.76	−0.11	−0.19	1.00									
CFER	−0.76	0.95	−0.76	−0.12	−0.17	0.98	1.00								
Size	−0.09	0.13	−0.08	−0.47	−0.06	0.11	0.14	1.00							
BM	0.01	0.01	0.00	−0.05	0.00	−0.01	−0.01	−0.08	1.00						
Beta	−0.03	0.00	0.02	0.34	−0.03	0.00	0.00	−0.07	0.00	1.00					
IdioVol	0.01	−0.08	0.06	0.67	0.00	−0.06	−0.08	−0.46	−0.07	0.28	1.00				
Momentum	0.00	0.00	−0.03	0.05	0.03	0.00	0.02	0.01	−0.04	0.02	0.21	1.00			
Reversal	0.06	−0.05	0.01	0.00	0.07	−0.05	−0.04	0.02	−0.02	0.02	0.06	0.25	1.00		
BidAsk	0.08	−0.11	0.04	0.13	0.05	−0.12	−0.13	−0.28	0.02	0.01	0.13	−0.04	−0.02	1.00	
Amihud	0.07	−0.10	0.03	0.21	0.06	−0.10	−0.12	−0.44	0.03	0.02	0.22	−0.04	0.03	0.31	1.00

Table 8: Fama-MacBeth (1973) Regressions

The table presents the results of Fama-MacBeth (1973) regressions in which the dependent variable is the excess stock returns over month t. The first regression (column (1)) includes the IV spread as the main explanatory variable along with control variables capturing various stock characteristics. The second one ((2)) replaces the IV spread with the excess put early exercise premium (ExPrem) and an orthogonalized part of the IV spread (IVSpread$^{\varepsilon}$) which is independent from the impact of excess premiums on IV spreads. The third regression ((3)) adds the orthogonalized parts of the price pressure (DOTS$^{\varepsilon}$) and friction (CFER$^{\varepsilon}$) measures respectively from Goncalves-Pinto et al. (2020) and Hiraki and Skiadopoulos (2023), both independent from the impacts of excess premiums and IVSpread$^{\varepsilon}$s on their corresponding original measures. The fourth regression ((4)) adds the volatility-of-variance (VoV) from Baltussen et al. (2018) while the fifth ((5)) further includes the ex-ante mean jump-size ($JumpSize$) from Yan (2011). The control variables include: size, the book-to-market ratio (BM), the beta of the stock, idiosyncratic volatility (IdioVol), momentum, reversal, stock bid-ask spread and the Amihud (2002) stock illiquidity measure. See the captions of Tables 1 and 7 for the definitions of all independent variables. Independent variables are measured at the stock level and dated $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

	Regression Models:				
	(1)	(2)	(3)	(4)	(5)
ExPrem		−0.34	−0.36	−0.35	−0.17
		[−5.98]	[−5.90]	[−6.16]	[−1.59]
IVSpread	0.73				
	[5.42]				
IVSpread$^{\varepsilon}$		0.73	0.71	0.74	0.22
		[2.61]	[2.38]	[2.69]	[0.86]
$JumpSize$					−0.55
					[−2.07]
VoV				−0.16	−0.13
				[−1.21]	[−0.98]
DOTS$^{\varepsilon}$			0.12	0.12	0.10
			[2.40]	[2.32]	[1.84]
CFER$^{\varepsilon}$			−0.23	−0.18	−0.17
			[−0.69]	[−0.55]	[−0.52]
Size	−0.11	−0.12	−0.11	−0.10	−0.10
	[−1.64]	[−1.80]	[−1.64]	[−1.47]	[−1.46]
BM	0.57	0.21	0.04	0.30	0.33
	[1.33]	[0.47]	[0.08]	[0.69]	[0.75]
Beta	0.13	0.04	−0.02	0.14	0.13
	[0.06]	[0.02]	[−0.01]	[0.06]	[0.06]
IdioVol	−0.12	−0.12	−0.12	−0.11	−0.10
	[−3.28]	[−3.26]	[−3.16]	[−2.96]	[−2.79]
Momentum	0.96	0.93	0.87	0.70	0.64
	[0.34]	[0.33]	[0.31]	[0.25]	[0.23]
Reversal	−0.34	−0.38	−0.26	−0.31	−0.33
	[−0.44]	[−0.50]	[−0.34]	[−0.40]	[−0.43]
BidAsk	−0.11	−0.11	−0.11	−0.11	−0.12
	[−2.64]	[−2.65]	[−2.59]	[−2.59]	[−2.66]
Amihud	−0.50	−0.38	−0.17	−0.19	−0.19
	[−0.40]	[−0.31]	[−0.14]	[−0.16]	[−0.17]
Intercept	2.68	2.82	2.71	2.55	2.57
	[2.45]	[2.55]	[2.41]	[2.23]	[2.26]

Table A.1: Definitions of the Explanatory Variables

The table presents the definitions of all the explanatory variables we use in our study. Our jump variables include: a left-tail variation measure ($Jump_{LT}$) and a mean jump-size proxy ($Jump_{Size}$). Our SV variables include a volatility of variance measure (VoV). All jumps and SV variables are either option-based or option-implied, hence contain the ex-ante information about the underlying stock. We also include a stock mispricing and a stock market friction measure (DOTS and CFER, respectively). In column (1), we include the names of these variables, while in column (2), we mention the authors who first proposed them along with their study year. We finally provide the variable definitions in column (3) where we also mention the appropriate references and page numbers from the original studies based on which we constructed these variables.

#	Variable	Authors & Year	Variable Definition
1	$JumpLT$	Bollerslev & Todorov (2011)	OTM ($K/S = 0.90$) put, scaled by the underlying stock, both adjusted for put's remaining maturity. Put price is taken from the implied volatility (IV) surface (Eq (18), p.2174).
2	$JumpSize$	Yan (2011); Cremers et al. (2015)	Difference in IVs of 30-day OTM put ($\Delta = -0.4$) and 30-day ATM call ($\Delta = 0.5$). IVs are taken from the IV surface (Eq (9), p.220; Sec IV.B, p.603).
3	VoV	Baltussen et al. (2018)	Standard deviation (SD) of the daily IVs for 30-day ATM put over the prior month, scaled by the average of those daily IVs. IVs are taken from the IV surface (Eq (1), p.1618).
4	DOTS	Goncalves-Pinto et al. (2020)	At the option level, the difference between stock's call-put implied value and its market price. For the stock level, we weight option-level measures using bid-ask spreads of each call-put pair written on the stock (Eq (3) & (4), p.3908).
5	CFER	Hiraki & Skiadopoulos (2023)	At the option level, the difference between stock's call-put implied value and its market price, scaled by gross risk-free to option time-to-maturity ratio. For the stock level, we weight option-level measures using option open interests written on the stock (Eq (6) & (7), pp.6-7).

Internet Appendix:

Early Exercise, Implied Volatility Spread and Future Stock Return: Jumps Bind Them All

This internet appendix includes supplementary simulation evidence and empirical test results to further support the analysis of our main paper. In Section IA.1, we undertake the Monte-Carlo based simulation exercise once again to show that excess premiums (IV spreads) still demonstrate positive (negative) trend with the mean jump-size μ_S even when option moneyness is different, option has a longer time-to-maturity or the underlying asset has a higher initial volatility. In Section IA.2, we show the suitability of the IV slope-based μ_S proxy that we employ in our empirical works. In Section IA.3, we repeat our main univariate portfolio sort exercise, but with the GBM-world early exercise premium and also with the total premium, instead of the excess premium. In Section IA.4, we show that our evidence for excess premiums' stock return predictability do not vary across different time periods in our sample, while in Section IA.5, we also validate our main empirical results under different sort-styles. In Section IA.6, we examine whether our results survive when we group options into various moneyness and maturity categories. Finally, in Section IA.7, we conduct an additional set of robustness checks to further strengthen our empirical findings.

IA.1 Simulations Under Different Moneyness, Maturity and Asset Volatility Levels

In the simulations of our main paper (see Section 2), we observe theoretical patterns of excess premium and IV spread across SV and SVJ parameters while assuming an ATM-only options, with

30 days-to-maturity and a 20% initial underlying asset volatility level. In this section, we explore whether those patterns still remain under a varying moneyness, maturity or asset volatility. To this end, we repeat our Longstaff-Schwartz (2001) based exercise either with a different moneyness level (Figure IA.1), or with a longer maturity or a higher asset volatility level (Figure IA.2), while keeping all other parameter values same as their basecases described in Section 2.2 of the main paper. In Figure IA.1, we show the results for ITM (strike-to-stock price ratio = 1.05; Panel A) and OTM (0.95; Panel B) options, while in Figure IA.2, the results are for the options with 60 days-to-maturity (Panel A) and with a 40% initial underlying asset volatility (Panel B). In sub-panels 1 of both figures, we show the excess premium and IV spread under the SV-world and across the σ_V, while in sub-panels 2 and 3, we show those two under the SVJ-world and across the μ_S and λ, respectively. In all figures, we calculate excess premium as the percentage of GBM-world American put value.

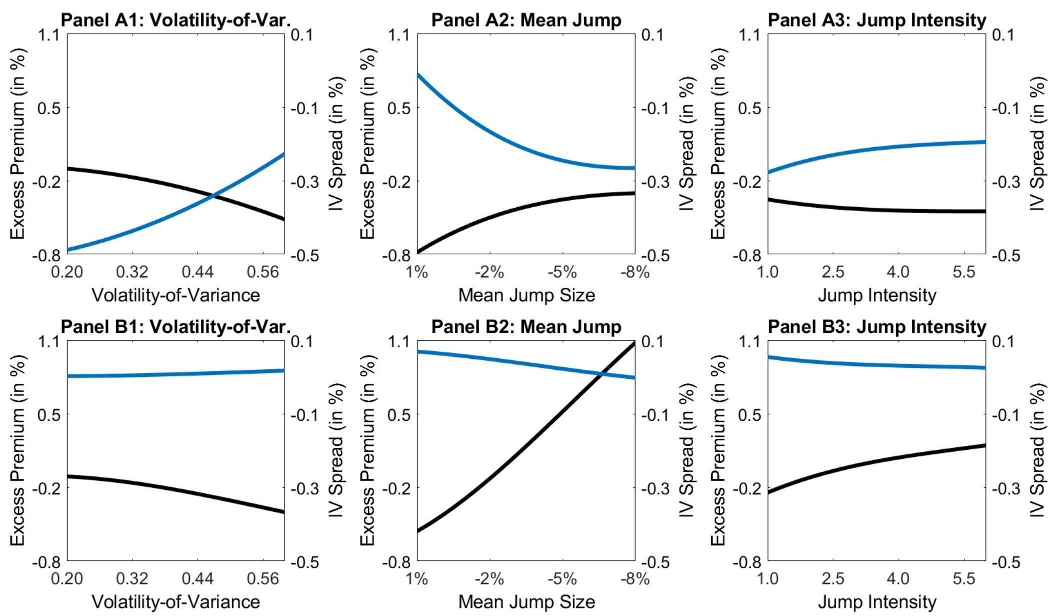

Figure IA.1: Excess Premiums and IV Spreads With Different Option Moneyness The figure plots simulated excess premiums (solid black) and IV spreads (solid blue) across σ_V, μ_S and λ parameters for ITM (Panel A) and OTM (Panel B) options. In each sub-panel, we put parameter values on the x-axis, while set excess premiums on the left and IV spreads on the right y-axes. We describe basecase parameter values in Section 2.2 of our main paper.

Figures IA.1 and IA.2 reveal that both excess premium and IV spread follow similar patterns with

σ_V, μ_S and λ regardless of option moneyness and time-to-maturity. For an ITM or OTM options, and also for an ATM with 60 days-to-maturity, the excess premium (IV spread) is still positively (negatively) related with μ_S and λ,[1] while negatively (positively) related with σ_V. Furthermore, the magnitude is also comparable. For instance, for a 60-day ATM put, excess premium increases from -0.67% to 0.43% as we increase the mean jump-size μ_S from 1% to -8% (in absolute term). For that same increase in μ_S, excess premium for a 30-day ATM put increases from -0.61% to 0.35% (see, Panel B of Figure 1 in our main paper).

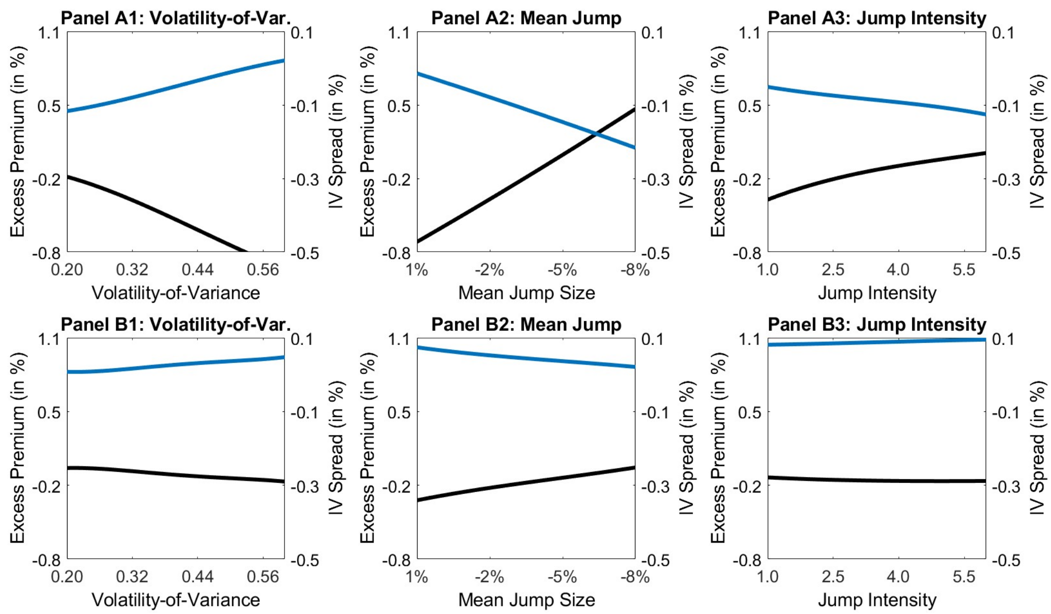

Figure IA.2: Excess Premiums and IV Spreads With Longer Maturity or Higher Asset Volatility The figure plots simulated excess premiums (solid black) and IV spreads (solid blue) across σ_V, μ_S and λ parameters for options with a longer time-to-maturity (60-Day; Panel A) and a higher underlying asset volatility (40%; Panel B). In each sub-panel, we put parameter values on the x-axis, while set excess premiums on the left and IV spreads on the right y-axes. We describe the basecase parameter values in Section 2.2 of our main paper.

Finally, Panel B of Figure IA.2 shows that excess premium (IV spread) follows a similar increasing (decreasing) trend with μ_S while a decreasing (increasing) trend with σ_V even when the initial underlying asset volatility is higher. Nevertheless, the magnitude of these changes is attenuated

[1]The only exception, in this case, is the excess premium and IV spread dynamics with jump-intensity λ for a 30-day ITM options with 20% initial asset volatility level (see Panel A3 in Figure IA.1).

when we compare them to their lower-volatility counterparts. With λ, the changes in both premiums and spreads are mostly flat with a higher volatility level.

Altogether, this section confirms that the patterns we observe in Figure 1 of our main paper can also be seen with different option moneyness, maturity or underlying asset volatility level.

IA.2 Suitability of the Empirical Mean Jump-Size Proxy

Following Yan (2011), in our main paper, we rely on the implied volatility difference between an OTM put and an equivalent ATM call ("IV Slope"), both with 30 days-to-maturity, as our proxy measure for the mean jump-size parameter μ_S. In this section, we further confirm, via theoretical simulations, whether that IV slope truly reflects the change in μ_S.

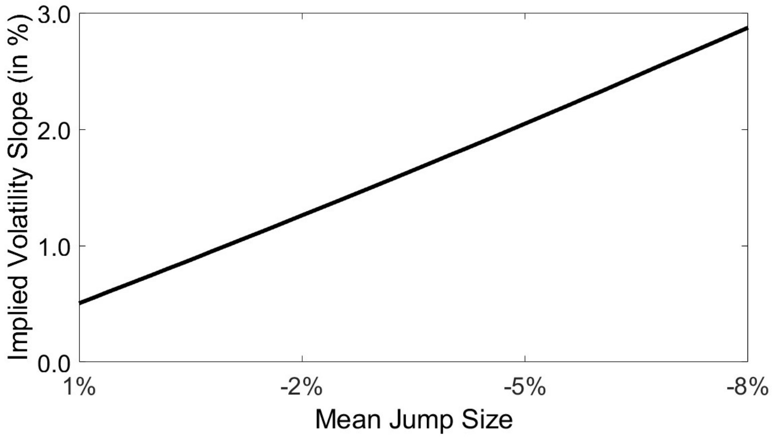

Figure IA.3: IV Slopes Plotted Against the Mean Jump-Size The figure plots the simulated IV slopes from 30-day maturity options across the mean jump-size μ_S under the SVJ model. We put μ_S on the x-axis, while keeping the IV slope on the y-axis. We describe the basecase parameter values for simulations in Section 2.2 of our main paper.

For 30-day maturity options, Figure IA.3 shows that IV slopes clearly relate with the mean jump-size with a steep gradient of around 0.26. The figure thus points that the slope, highlighted in Yan (2011), remains a very good proxy of the mean jump-size in theory.

IA.3 Return Predictability With the Total and the GBM Premium

In Section 3.2 of the main paper, we show how we decompose the total early exercise premium of a put into its excess and GBM-world premium parts. Although the excess premium became our main predictor variable throughout the paper, we can however consider the total premium as a proxy of that excess premium. As options are redundant assets under the GBM world (see Coval and Shumway (2001), for instance), any early exercise under this world should not carry any information about the future underlying stock price movement. Given that the total premium also embeds the GBM-world premium, the total premium would hence become a noisy proxy of the excess premium. To test the conjecture that GBM-world premiums should not predict future returns and also to check whether total premiums have any predictability, we undertake a univariate portfolio sort exercise in this section. Similar to our univariate sorts in the main paper, at the end of each sample month $t-1$, we separately sort stock-level total and GBM-world premiums into quintile portfolios. We also form "High–Low" spread portfolios along each sort dimension. We hold all portfolios over month t and report both their equal-weighted and value-weighted mean excess returns.

TABLE IA.1 ABOUT HERE

Table IA.1 reports the results from this portfolio sort exercise. From the table, we observe that although the total premium is a noisy proxy, it can still significantly predict future stock returns. The equal (value) weighted excess mean return for the "High–Low" portfolio, for instance, sorted on the total premium stands at −1.18% (−0.63%) with a t-statistic of −7.01 (−3.46). In contrast, when sorted on the GBM-world premium, the spread portfolio return becomes insignificant, in line with our conjecture.

Additionally, when calculating American option IVs, Optionmetrics employs the CRR model which already includes the early exercises induced under the GBM world.[2] Hence, while the excess premium of an American put and the IV spread of an equivalent American option pair can be

[2] See the 2023 IvyDB US Reference Manual from OptionMetrics.

related (recall our simulation exercise and empirical evidence from the main paper), the GBM-world premium should not show any significant association with the IV spread. Indeed, we find that is the case. The mean cross-sectional correlation between the GBM-world premium and the IV spread stands at around 6% in our data sample, considerably lower and in opposite direction than the correlation between excess premium and the spread (see Table 7 of the main paper).

Overall, this section provides further evidence that any excess part of the total premium mainly drives the return predictability that we document in the main paper. The predictive ability of the GBM premium is insignificant.

IA.4 Portfolio Sort Exercise Across Different Time Periods

We next test whether excess premiums' stock return predictability that we show in our main paper varies over time. As Cremers and Weinbaum (2010) suggest, the predictability of IV spreads declines in the recent time due to less stock mispricing and lower informed trading activities during this period. Our simulation exercise in Section 2.2 and main empirical evidence show a link between the IV spread and the excess premium. Hence, any decline in IV spreads' return predictive power over time should also translate to a decline in excess premiums' predictability if informed trading or mispricing is the channel. To check this, we conduct separate univariate portfolio sort exercise in Table IA.2 using the excess premium over two sub-periods: for the 1996-2008 and for the 2008-2016 period. Same as before, we sort the stock universe into quintile portfolios and create a "High–low" spread portfolio at the end of the sample month $t-1$ of a sub-period. We hold all portfolios over month t and calculate their equal and value-weighted excess mean returns.

Table IA.2 About Here

The table clearly highlights that excess premiums' return predictability does not diminish with time. During the 1996-2008 period, the mean excess return for the equal-weighted "High–Low" spread portfolio, for instance, is −1.17% (t-statistic: −5.35), which remains very similar, to −1.20% (t-statistic: −5.04), during the 2008-2016 period. Consequently, the results here provides further support to our empirical evidence in Section 4.5 that the predictive ability of excess premiums are not primarily driven by investors' informed trading activities or mispricing of the underlying stocks.

IA.5 Tercile and Decile Portfolio Sort Exercise

In Table IA.3, we further investigate whether sorting the stock universe based on the tercile or decile breakpoints of the excess premium can change the results of our main paper. To this end, we again conduct the univariate portfolio sort exercise using excess premiums. However, instead of sorting the stocks into quintile portfolios at the end of each sample month $t-1$, we sort them into either tercile (Panel A) or decile (Panel B) portfolios. We further create the "High–Low" spread portfolio along each sort dimension. We finally hold all portfolios over month t and calculate their equal-weighted and value-weighted mean excess returns.

Table IA.3 About Here

The table suggests that our main empirical evidence with excess premiums' return predictability is not driven by our choice of the sorting style. For instance, the mean excess returns for the equal-weighted "High–Low" spread portfolio from the tercile and decile sorts are −1.01% (t-statistic: −7.00) and −1.44% (t-statistic: −6.02), respectively. These returns are comparable to the −1.18% (t-statistic: −7.25) return for that same portfolio under the quintile portfolio sort (compare Table IA.3 with Table 3 from the main paper).

IA.6 Option Moneyness and Time-to-Maturity

In the empirical tests of our main paper, we calculate the stock-level excess premium using put open interest as the weighting variable, regardless of the individual put's moneyness and time-to-maturity.

Here, we examine whether our findings on the ability of excess premiums to predict stock returns are driven by any specific moneyness and/or time-to-maturity. The simulation evidence in Sections 2 and IA.1 suggest that mean jump-size μ_S can drive the excess premium for puts from various moneyness and/or maturity categories. Hence, if μ_S is the main driver, we should expect return predictability for excess premiums calculated from different moneyness and time-to-maturity puts, not just from puts in one category. At the end of each sample month $t-1$, we split put observations into double-sorted portfolios according to their moneyness and time-to-maturity. Specifically, we first sort the puts into ITM, ATM and OTM portfolios.[3] Within each portfolio, we further split puts according to whether their time-to-maturity lies below or above 45 days. The intersection yields the double-sorted portfolios. We then use observations from each of these portfolios to calculate stock-level excess premiums, from which we form quintile portfolios and hold them over month t.

TABLE IA.4 ABOUT HERE

The results in Table IA.4 suggest that excess premiums calculated from different moneyness-maturity put observations can significantly predict the cross section of future stock returns. For instance, when we calculate excess premiums from ATM puts with less than 45 days-to-maturity (Panel B), and then conduct the sort, the average excess return for the "High−Low" portfolio stands at −1.19% (t-statistic: −5.83). In contrast, when we calculate those premiums from ITM puts with that same maturity (Panel A), the spread portfolio still remains significant, with a mean of −2.03% (t-statistic: −3.50).The results in the table thus suggest that the predictive ability of the excess premium is not confined to puts from any specific moneyness-maturity portfolio, in line with the jump-based explanation for this predictability.

[3] We define a put as ITM if its strike-to-stock ratio is greater than 1.05. A put is treated as ATM if this ratio is in between 0.95 and 1.05, and as OTM if the ratio is less than 0.95.

IA.7 Further Robustness Checks

We finally conduct additional tests in Table IA.5 to show the robustness of our main empirical results. We start by examining whether the findings are due to our choice of calculating the GBM-world American put price under the CRR method. To address this, we calculate the excess premium as the difference in exchange-traded American put price and its equivalent theoretical GBM-world price, where we compute the theoretical price using either Longstaff and Schwartz's (2001) LSM (following Section 2) or the Finite Difference method (Panel A). We also examine whether option liquidity can impact our results and conduct our empirical test using a sub-sample made only from positive trade volume option observations (Panel B). We further check whether an alternative definition of the stock-level excess premium and IV spread can impede the return predictability in our main results. To this end, we follow Shang (2017) and calculate weighted average stock-level premiums using the dollar value of open interest rather than the number of contracts outstanding (Panel C). We further check whether our findings are driven by the separate closing times for stock and option markets. This nonsynchronicity issue, as shown in the literature (see, for example, Battalio and Schultz (2006)), can drive violations of put-call parity in the market, thereby allowing for wider implied volatility spreads and excess premiums for exchange-traded American options. To control for the nonsynchronicity issue, we sort stocks into portfolios at the end of each month $t-1$, but only start cumulating returns from the next day, thus avoiding the overnight return from the holding month return (Panel D). We finally examine whether the predictability we find is persistent by using a two-month holding period for the portfolios (Panel E).

TABLE IA.5 ABOUT HERE

The results in Panel A suggests that the predictive ability of excess premiums is not due to our reliance on the CRR method. Using either the LSM or FD method, the mean return for the excess premium-sorted "High−Low" portfolio, for instance, remains virtually identical to the −1.18%

return for that same portfolio under the CRR method. The difference in their t-statistics is also negligible (compare with Table 3 from the main paper). Furthermore, using only the positive trade volume option observations or utilizing the dollar value of open interests to calculate option-level weights also does not change our earlier empirical evidence. We observe a mean monthly spread portfolio return of -1.19% (t-statistic: -7.40), for instance, when using the dollar value of open interests (see Panel C). Besides, our results are not due to the nonsynchronicity between stock and options market closures. Excluding the overnight returns still delivers a mean return of -1.17% per month (t-statistic: -7.26) on the "High−Low" portfolio when sorting on the excess premium (see Panel D). Finally, the results in Panel E indicate that the return predictability we document, to some extent, extends beyond the one-month holding horizon for our main tests, providing further evidence that short-term mispricing is not the main driver for the predictability.

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Table IA.1: Excess Returns from GBM and Total Premium-Sorted Portfolios

The table presents the equal-weighted (Panel A) and market-value weighted (Panel B) excess mean returns (both in %) sorted univariately and separately on the total put early exercise premium (Total Premium) and also on the premium under the GBM-world (GBM Premium). See the caption of Table 1 from the main paper for the definitions of these premiums. At the end of month $t-1$, we separately sort stocks into portfolios according to the quintile breakpoints of the premiums. We also form a spread portfolio long the top and short the bottom quintile ("High−Low") for each sort and hold all portfolios over month t. Observations are matched across both premiums and in both panels, so that all correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics, calculated using a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: Equal-Weighted Evidence						
Total Premium	0.91	0.64	0.51	0.23	−0.27	−1.18
	[2.16]	[1.39]	[1.16]	[0.54]	[−0.66]	[−7.01]
GBM Premium	0.23	0.37	0.49	0.30	0.55	0.32
	[0.47]	[0.87]	[1.21]	[0.68]	[1.23]	[1.60]
Panel B: Value-Weighted Evidence						
Total Premium	0.80	0.68	0.49	0.37	0.18	−0.63
	[2.02]	[1.66]	[1.21]	[0.93]	[0.44]	[−3.46]
GBM Premium	0.29	0.25	0.27	0.48	0.74	0.45
	[0.53]	[0.59]	[0.67]	[1.22]	[1.94]	[1.64]

Table IA.2: Excess Premium Sort Exercise Over Different Periods

The table presents the equal-weighted (Panel A) and market-value weighted (Panel B) excess mean returns (both in %) univariately sorted on the stock-level excess put early exercise premium ("Excess Premium") over different time periods. See the caption of Table 1 from the main paper for the definition of excess premium. At the end of month $t-1$ within each period, we sort stocks into portfolios according to the quintile breakpoints of the excess premium. We also form spread portfolios long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. Observations in both panels within a time-period are matched, so that all correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics, calculated using a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: Equal-Weighted Evidence						
1996-2008	0.56	0.25	0.00	−0.20	−0.61	−1.17
	[0.91]	[0.38]	[0.00]	[−0.31]	[−1.04]	[−5.35]
2009-2016	1.52	1.42	1.28	1.06	0.33	−1.20
	[3.61]	[3.14]	[2.33]	[2.15]	[0.60]	[−5.04]
Panel B: Value-Weighted Evidence						
1996-2008	0.44	0.31	0.09	−0.04	−0.22	−0.66
	[0.74]	[0.50]	[0.15]	[−0.06]	[−0.38]	[−2.82]
2009-2016	1.51	1.27	1.15	1.20	0.74	−0.77
	[3.61]	[3.38]	[2.63]	[3.25]	[1.90]	[−3.04]

Table IA.3: Excess Premium - Tercile and Decile Portfolio Sorts

The table presents the equal-weighted (EW) and market-value weighted (VW) excess mean returns (both in %) univariately sorted on the stock-level excess put early exercise premium ("Excess Premium"). See the caption of Table 1 from the main paper for the definition of excess premium. At the end of month $t-1$, we sort stocks into portfolios according to either the tercile (Panel A) or the decile (Panel B) breakpoints of the excess premium. We also form spread portfolios long the top and short the bottom tercile/decile ("High−Low") and hold all portfolios over month t. Observations are matched across the weighting schemes, so that all correspond to the same underlying stock at $t-1$. The numbers in square parentheses are Newey and West (1987) t-statistics, calculated using a twelve-month lag length.

Panel A: Tercile Portfolio Sort

	Low	2	High	High–Low
EW	0.86	0.48	−0.16	−1.01
	[2.01]	[1.09]	[−0.38]	[−7.00]
VW	0.84	0.46	0.17	−0.67
	[2.18]	[1.14]	[0.41]	[−4.71]

Panel B: Decile Portfolio Sort

	Low	2	3	4	5	6	7	8	9	High	High–Low
EW	0.92	0.89	0.76	0.59	0.39	0.53	0.43	0.08	−0.03	−0.52	−1.44
	[2.26]	[2.05]	[1.69]	[1.29]	[0.83]	[1.19]	[0.98]	[0.18]	[−0.07]	[−1.19]	[−6.02]
VW	0.83	0.85	0.88	0.47	0.60	0.40	0.50	0.25	0.15	0.07	−0.75
	[2.29]	[1.99]	[2.17]	[1.02]	[1.45]	[0.95]	[1.32]	[0.60]	[0.38]	[0.18]	[−3.45]

Table IA.4: Excess Premium - Controlling for Moneyness and Time-to-Maturity

The table presents the mean excess percentage returns of equal-weighted stock portfolios sorted on the excess put early exercise premium ("Excess Premium"), measured at the stock level. See the caption of Table 1 from the main paper for the definition of excess premium. We calculate a number of excess premiums for each individual stock using option observations from various moneyness and time-to-maturity categories. At the end of each sample month $t-1$, we first sort options 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 or over 45 days. For each stock, we then use option observations from each of these moneyness and time-to-maturity-sorted portfolios separately to calculate stock-level excess premiums. We finally sort stocks into portfolios separately according to the quintile breakpoints of each version. We also form separate spread portfolios long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

Days-to-Maturity (DTM)	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: In-The-Money (Strike-to-Stock Price > 1.05)						
$\text{DTM} \leq 45$	0.54	0.53	0.12	0.42	−1.49	−2.03
	[0.74]	[0.87]	[0.18]	[0.64]	[−2.52]	[−3.50]
$45 < \text{DTM} \leq 90$	0.64	0.44	0.46	0.05	−0.61	−1.25
	[1.17]	[0.84]	[0.86]	[0.09]	[−1.17]	[−3.93]
Panel B: At-The-Money (Strike-to-Stock Price 0.95 to 1.05)						
$\text{DTM} \leq 45$	0.94	0.60	0.38	0.29	−0.26	−1.19
	[2.25]	[1.28]	[0.78]	[0.62]	[−0.65]	[−5.83]
$45 < \text{DTM} \leq 90$	0.87	0.46	0.50	0.32	−0.27	−1.13
	[2.05]	[0.97]	[1.08]	[0.72]	[−0.64]	[−7.29]
Panel C: Out-Of-The-Money (Strike-to-Stock Price < 0.95)						
$\text{DTM} \leq 45$	0.52	0.37	0.42	0.16	−0.92	−1.45
	[0.83]	[0.59]	[0.57]	[0.27]	[−1.70]	[−4.77]
$45 < \text{DTM} \leq 90$	0.54	0.41	0.52	0.15	−0.64	−1.18
	[1.09]	[0.79]	[0.95]	[0.28]	[−1.32]	[−4.22]

Table IA.5: Additional Robustness Tests

The table presents the mean excess percentage returns of equal-weighted stock portfolios, univariately sorted on the stock-level excess premium (in all panels), and also on the IV spread and an orthogonalized IV spread variable denoted with an ε superscript (Panels B to E). See the caption of Table 1 from the main paper for the definition of excess premium and IV spread. At the end of month $t-1$, we sort stocks into portfolios according to the quintile breakpoints of the sorting variables. We also form a spread portfolio long the top and short the bottom quintile ("High−Low") and hold all portfolios over month t. We first rely on either the Longstaff and Schwartz (2001) least squares Monte-Carlo (LSM) scheme or the finite difference (FD) scheme to calculate the GBM-world theoretical American put price and the subsequent excess premium at the option and stock level (Panel A). We next return to the original definition for option-level sorting variables, but calculate their stock-level counterparts only using positive trade volume options (Panel B) We further use dollar value of open interests as weights to calculate stock-level sorting variables (Panel C). We again use open-interest-weights for the sorting variables but cumulate stock returns for each portfolio from the next day rather than from the portfolio formation day, thus excluding the overnight return (Panel D). We finally show the returns for the portfolios over the second month after portfolio formation (Panel E). The numbers in square parentheses are Newey and West (1987) t-statistics with a twelve-month lag length.

	1 (Low)	2	3	4	5 (High)	High−Low
Panel A: Theoretical American Put Price Under Alternative Numerical Schemes						
Excess Premium [LSM]	0.90	0.67	0.46	0.25	−0.27	−1.17
	[2.14]	[1.53]	[1.02]	[0.58]	[−0.67]	[−6.91]
Excess Premium [FD]	0.91	0.69	0.45	0.23	−0.26	−1.17
	[2.19]	[1.54]	[1.00]	[0.53]	[−0.64]	[−7.02]
Panel B: Sample with Only Positive Option Trade Volume Observations						
Excess Premium	0.90	0.46	0.29	0.26	−0.59	−1.49
	[1.88]	[0.87]	[0.53]	[0.54]	[−1.29]	[−7.40]
IV Spread	−0.72	0.22	0.45	0.63	0.73	1.45
	[−1.43]	[0.42]	[0.88]	[1.34]	[1.49]	[7.15]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.32	0.38	0.50	0.43	0.31	0.63
	[−0.62]	[0.63]	[0.98]	[1.01]	[0.70]	[3.26]
Panel C: Using Dollar ($) Open Interest Weights						
Excess Premium	0.91	0.64	0.49	0.26	−0.28	−1.19
	[2.25]	[1.40]	[1.07]	[0.60]	[−0.70]	[−7.40]
IV Spread	−0.45	0.24	0.58	0.78	0.86	1.30
	[−0.97]	[0.54]	[1.41]	[1.90]	[2.01]	[7.44]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.09	0.45	0.49	0.70	0.47	0.56
	[−0.17]	[0.93]	[1.16]	[1.81]	[1.25]	[2.83]
Panel D: Excluding Overnight Returns						
Excess Premium	0.91	0.67	0.46	0.25	−0.27	−1.17
	[2.17]	[1.50]	[1.02]	[0.58]	[−0.66]	[−7.26]
IV Spread	−0.45	0.22	0.63	0.78	0.83	1.29
	[−0.98]	[0.51]	[1.55]	[1.90]	[1.95]	[7.54]
IV Spread$^{\varepsilon}$(Excess Premium)	−0.03	0.39	0.52	0.66	0.49	0.52
	[−0.06]	[0.82]	[1.27]	[1.72]	[1.29]	[2.57]
Panel E: Return Predictability on the Second Month						
Excess Premium	0.50	0.52	0.36	0.52	0.21	−0.30
	[1.20]	[1.17]	[0.78]	[1.27]	[0.53]	[−2.16]
IV Spread	0.07	0.51	0.57	0.62	0.34	0.27
	[0.17]	[1.20]	[1.41]	[1.47]	[0.78]	[2.12]
IV Spread$^{\varepsilon}$(Excess Premium)	0.16	0.52	0.43	0.58	0.43	0.27
	[0.33]	[1.12]	[1.03]	[1.51]	[1.10]	[1.47]