The Contribution of Frictions to Expected Returns*

Kazuhiro Hiraki† George Skiadopoulos‡

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Abstract

We derive a model-free option-based formula to estimate the contribution of market frictions to expected returns (CFER) within an asset pricing setting. We estimate CFER for the U.S. optionable stocks. We document that CFER is sizable, it predicts stock returns and it subsumes the effect of frictions on expected returns as expected theoretically. The sizable alpha of a long-short portfolio formed on CFER is consistent with the size of market frictions and it is not due to model mis-specification. Moreover, we show that various option-implied measures proxy CFER, thus providing a theoretical explanation for their ability to predict stock returns.

JEL classification: C13, G12, G13

Keywords: Alpha, Asset pricing, Implied volatility spread, Limits of arbitrage, Market frictions, Return predictability

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†School of Economics and Finance, Queen Mary University of London, Mile End Road, London, E1 4NS, UK. k.hiraki@qmul.ac.uk

‡School of Economics and Finance, Queen Mary University of London, Mile End Road, London, E1 4NS, UK, and Department of Banking and Financial Management, University of Piraeus, 80, Karaoli and Dimitriou Str, Piraeus, Greece. Also Associate Research Fellow with Cass Business School, City University of London and Warwick Business School, University of Warwick. g.skiadopoulos@qmul.ac.uk and gskiado@unipi.gr

1 Introduction

In a frictionless market, asset expected returns are determined by the covariance risk premium proxied empirically by a number of risk factors. However, in the presence of market frictions such as margin constraints, short-sale constraints and transaction costs asset expected returns will also be determined by the *contribution of frictions to expected returns* (CFER). The estimation of CFER is far from being trivial because it typically requires assumptions on the types of frictions and agents' preferences. We circumvent these obstacles and provide an option-based model-free formula to estimate the CFER of any optionable stock derived within a formal asset pricing setting. The estimation of CFER is of importance because CFER is inherently part of the expected return. Hence, its estimate can be used to predict asset returns. In addition, its estimate can reveal the impact of market frictions on expected returns and the dominant market frictions since theoretically CFER arises because of market frictions.

To derive our CFER formula, we structure our theoretical setting as follows. We consider a marginal agent who trades in both the stock and option market. We model market frictions as constraints on the agent's portfolio allocation, yet we do not specify neither the number nor the type of constraints.[1] The optimality condition of the agent yields an asset pricing model, where the expected excess return equals the covariance risk premium plus CFER which arises due to market frictions. In a frictionless market, the expected excess return should equal the risk premium required by the agent, otherwise buying (selling) a stock whose expected excess return is higher (lower) than the risk premium she demands would improve her utility. On the other hand, market frictions may prevent the agent from engaging in such an arbitrage strategy and hence the expected excess return can deviate from the covariance risk premium term even at equilibrium.

[1] The existence of such an agent is realistic and it is in line with the recent literature. For example, a number of studies document that financial intermediaries is the marginal investor who trades in various financial markets simultaneously (e.g., Adrian et al. (2014), He et al. (2017)), and the market frictions faced by intermediaries have important asset pricing implications (e.g., Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), He and Krishnamurthy (2018), among others).

This is formalized as the following asset pricing equation,

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}] - R_{t,t+1}^0 = CFER_{t,t+1} - \frac{Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1})}{\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*]}, \tag{1}$$

where $R_{t,t+1}$ and $R_{t,t+1}^0$ are the gross return of the stock and the risk-free bond from time t to $t+1$, respectively and $m_{t,t+1}^*$ is the intertemporal marginal rate of substitution (IMRS) of the agent under market frictions.[2] CFER measures the part of the expected excess return which is not explained by the covariance risk premium. Therefore, CFER is not a compensation for risks, but it solely captures the effect of market frictions; it is a function of the Lagrange multipliers of the respective constraints, and it does not depend on the IMRS.

Next, we show that a stock's CFER can be estimated as a scaled deviation from put-call parity. To derive this result, first we prove that CFER theoretically equals the sum of two terms; the first term is the degree of deviations from put-call parity scaled by the ratio of the gross risk-free rate to the current underlying stock price, and the second term is a function of the effect of market frictions on the market option prices. Then, we show that the size of the latter term is negligible compared to that of the first term, and hence CFER can be reliably estimated by the first term.[3]

Three remarks are in order regarding our approach to estimate CFER and the resulting formula. First, the relation between CFER and deviations from put-call parity is intuitive. Limits of arbitrage due to market frictions cause deviations from the law of one price (LoOP) (e.g., Gârleanu and Pedersen (2011)). Put-call parity is an example of LoOP between the underlying stock and a synthetic stock formed by a pair of European call

[2]There is another strand of literature on the limits of arbitrage, where no constraints on portfolio allocations are imposed and hence no CFER term appears (e.g., De Long et al. (1990), Greenwood (2005), Gabaix et al. (2007), Vayanos and Woolley (2013); see for a survey Gromb and Vayanos (2010)). Instead, this strand of literature views the risk-averseness of the agents as a friction. This approach is distinct from ours because the alternative approach does not render deviations from the law of one price, which is a key ingredient of our option-based estimation formula of CFER.

[3]While the first term of the theoretical CFER formula can be calculated in a model-free manner, one needs to make assumptions on the type of frictions and the associated effect of frictions on option prices to calculate the second term. In Appendix C, we investigate the magnitude of the latter term under three alternative ways of modeling the effect of frictions on option prices proposed by the previous literature, and we document that the latter term is negligible for all cases.

and put options with the same strike and time-to-maturity. Therefore, deviations from put-call parity contain information about the degree of market frictions faced by the agent. However, our CFER estimation formula shows that deviations from put-call parity (i.e., deviations in *price levels*) should be scaled in order to use the embedded information to measure CFER, which is part of expected *returns*. Second, our approach to estimate CFER is model-free in that no option pricing model or parameter estimation is required, and the derivation of the theoretical relation between CFER and deviations from put-call parity requires no assumptions on the agent's preferences nor on the type of frictions. Therefore, the estimated CFER does not reflect any effect from risk factors which may drive the agent's IMRS and it solely captures the effect of frictions. This is in line with the theoretical foundation of CFER in equation (1) and in line with the results in Gârleanu and Pedersen (2011), who show that deviations from LoOP do not depend on the IMRS. Finally, the fact that we are agnostic about the type of frictions which affect asset returns allows developing a reverse engineering approach to study the effect of market frictions on stock returns. Rather than first postulating the possible types of frictions and then measure their effect on stock returns, we estimate CFER first and then we examine how it covaries with various proxies of market frictions. This will reveal the type of frictions which predominantly give rise to CFER. This reverse approach is robust because it is founded theoretically. CFER measures the *overall* effect of market frictions on expected returns by circumventing model mis-specification concerns. In addition, CFER arises due to market frictions and hence various types of frictions should covary with it. Therefore, our approach allows us to learn about frictions from CFER.

We estimate CFER for each optionable U.S. common stock from January 1996 to April 2016. Four are the main empirical findings. First, the estimated CFER can become sizable, ranging from -1.24% to 0.89% per month in a 5th to 95th percentile range; CFER can become twice as large in magnitude as the average U.S. equity premium (0.5% per month; Mehra (2012)). This result also implies that there is considerable variation in stocks' expected returns due to market frictions.

Second, we document that CFER predicts future excess stock returns cross-sectionally as equation (1) predicts; the expected return should increase as CFER increases. We find that a long-short spread portfolio of the CFER-sorted value-weighted decile portfolios, where we long the portfolio of stocks with the highest CFER and short the portfolio of the stocks with the lowest CFER, yields a positive and statistically significant average return of 164 bps per month (t-stat: 5.76). Risk-adjusted returns with respect to standard asset pricing models are also sizable and statistically significant. For example, the Carhart (1997) four-factor alpha of the spread portfolio is 186 bps per month (t-stat: 6.56). Our findings are robust to non-synchronous trading in the stock and equity option markets, the portfolio construction method (equally- or value-weighted), possible outliers in the estimated CFER and over alternative time periods. In addition, our results are robust to recent data snooping concerns (e.g., Harvey et al. (2016), Harvey (2017), Hou et al. (2017) thanks to the sufficiently high t-statistics even for the value-weighted portfolios and the formal theoretical foundation for CFER. We discuss further below that the performance of the CFER-based portfolio strategy is in line with the theoretical properties of CFER and a typical estimate of transaction costs. Interestingly, our findings show that CFER and its associated predictive power are sizable even for optionable stocks which tend to be big (Cremers and Weinbaum (2010)), that is, market frictions have a considerable effect even on the expected returns of big stocks.

Third, equation (1) implies that the regression of "CFER-adjusted excess returns," $R_{t,t+1} - R^0_{t,t+1} - CFER_{t,t+1}$ on risk factors should yield a zero intercept (i.e., an insignificant alpha). We test this hypothesis on portfolios sorted by CFER and find that it holds. The switch from significant alphas in the case where we regress excess returns on risk factors to insignificant alphas in the case where we regress the CFER-adjusted excess returns on risk-factors reinforces the evidence that the predictability of CFER originates from capturing the effect of market frictions, rather than from omitted risk factors.

Fourth, we show that the theoretical range of CFER values should be approximately equal to twice the round-trip transaction costs. The range of our estimated CFER values verifies this prediction: it approximately equals twice the estimated round-trip transaction costs for large optionable stocks (approximately 1%, see e.g., Lesmond et al. (1999) and Hasbrouck (2009)). In addition, the theoretically derived range of CFER values implies a theoretical upper bound of the alpha of the CFER-sorted spread portfolio; CFER has also an alpha interpretation because it is the part of the expected return which cannot be explained by the covariance risk premium. The theoretical range of CFER suggests that the upper bound of the average CFER of a CFER-sorted long-short portfolio should be approximately twice the round-trip transaction costs. This implies that the upper bound of the alpha of the CFER-sorted spread portfolio should be about 2%, that is, the limits of arbitrage for trading (even big) stocks are large enough to generate a 2% alpha per month. The empirical findings verify this prediction, too. Our estimated alphas of the CFER-sorted spread portfolio are below yet close to the upper bound implied by transaction costs. Therefore, the estimated alpha of CFER-sorted spread portfolio is consistent with the market frictions faced by investors.

Our theoretically derived range of CFER values also predicts that, for any given stock, the dispersion of CFER values should increase with the size of transaction costs (or more generally, with the size of market frictions). In line with this prediction, we find that CFER takes more extreme values (either very negative or very positive) for stocks which are subject to greater market frictions and that the variation of CFER increases over distressed periods. Moreover, the fact that we are agnostic about the type of market frictions and the theoretical foundation of CFER allows us to reverse engineer the dominant market frictions which affect the returns of optionable stocks. Fama and MacBeth (1973) regressions of CFER on a set of market frictions-related variables reveal that transaction costs are of major importance for explaining variations in CFER. We also find that the tighter short-sale constraints are, the more negative CFER is (i.e., the greater the expected underperformance of stocks relative to the covariance risk premium). This is in accordance with previous literature, which documents that stocks which are subject to short-sale constraints underperform (e.g., Ofek et al. (2004) and Drechsler and Drechsler (2014)), yet we find that the effect of short-sale constraints to CFER is of second order importance. This is expected because short sale constraints are less pronounced among the universe of big stocks like our optionable stocks (e.g., D'Avolio (2002) and Asquith et al. (2005)). The relation between CFER and proxies of *various* market frictions confirms that CFER originates from limits to arbitrage and that it is a "sufficient statistic" which subsumes the overall effect of any relevant market frictions on expected returns.

Our study is related to three strands of literature. First, it draws upon the theoretical literature on asset pricing under market frictions. Early studies by He and Modest (1995) and Luttmer (1996) examine whether the equity risk premium puzzle may be solved by taking market frictions into account. More recently, a strand of this literature develops asset pricing models by assuming *specific* frictions such as liquidity risk (Acharya and Pedersen (2005)), market and funding liquidity constraints (Brunnermeier and Pedersen (2009)), margin constraints (Gârleanu and Pedersen (2011), Chabakauri (2013)), margin and leverage constraints (Frazzini and Pedersen (2014)) and exclusion of strategies with possible unlimited losses (Jarrow (2016)). Our model is in line with these studies in that the Lagrange multipliers of binding constraints on agents' portfolio allocation affect expected returns. Our study is also related to Brennan and Wang (2010) and Hou et al. (2016), who propose a reduced form model of frictions/mispricing and asset pricing. Similar to our approach, these models make no assumption on the types of frictions, yet they make assumptions on the dynamics of mispricing and the specification of the IMRS to estimate the effect of mispricing/frictions on expected returns.

Our paper also complements empirical studies which examine the relation between the cross-section of stock returns and market frictions such as stock-level illiquidity (Amihud (2002)), short-sale constraints (e.g., Chen et al. (2002), Ofek et al. (2004), Asquith et al. (2005), Drechsler and Drechsler (2014)), "betting against beta" effect due to leverage constraints (Frazzini and Pedersen (2014), Jylhä (2018)), uncertainty about future shorting costs (Engelberg et al. (2018)), idiosyncratic volatility (Ang et al. (2006), Stambaugh et al. (2015)), delay in the response of prices to information (Hou and Moskowitz (2005)) and intermediaries' liquidity constraints (Nagel (2012)).[4] This strand of literature documents that specific friction-related variables predict stock returns cross-sectionally. We verify this finding using CFER, which encompasses the overall effect of any relevant market frictions on expected returns. Similarly, rather than using specific friction-related variables, Stambaugh et al. (2015) sort individual stocks into portfolios based on their "alpha" proxied by the average ranking of each stock across eleven anomalies. Our paper is similar to theirs in that our sorting variable, CFER, can be interpreted as alpha.

Finally, our research is pertaining to the literature on the informational content of option prices, especially to studies which document that measures based on deviations from put-call parity (Ofek et al. (2004), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Muravyev et al. (2016), Goncalves-Pinto et al. (2017)) predict future stock returns.[5] We contribute to this literature by showing that the properly scaled deviations of put-call parity, i.e. our CFER formula, is part of the expected returns under a formal asset pricing setting. Hence, we provide a theoretical explanation to the ability of measures of deviations from put-call parity to predict stock prices. Furthermore, we show theoretically that two popular measures, the implied volatility spread (the difference between call and put implied volatilities) (Bali and Hovakimian (2009), Cremers and Weinbaum (2010)), and Goncalves-Pinto et al.'s (2017) DOTS measure, proxy CFER. Consistently, we document that CFER has at least as good predictive power as these option-implied measures, as expected.

The rest of the paper is organized as follows. In Section 2, we provide the option-based formula to estimate CFER within our asset pricing model under market frictions. We also discuss the testable predictions of the model regarding CFER. Section 3 describes the data, the way we implement our formula to compute CFER, and the summary statistics

[4]See also Hou et al. (2017) for the list of more than 100 friction-related anomaly variables.

[5] Manaster and Rendleman (1982), Xing et al. (2010), Yan (2011), Chang et al. (2013), Conrad et al. (2013), An et al. (2014), Stilger et al. (2017), Martin and Wagner (2018) also study the informational content of market option prices to predict future stock returns; see also Giamouridis and Skiadopoulos (2011) and Christoffersen et al. (2013) for reviews.

of the estimated CFER. In Section 4, we study empirically the theoretical properties of CFER. In Section 5, we study the relation between CFER and other option-implied return predicting measures. Section 6 concludes and discusses the findings.

2 Theoretical framework

2.1 Asset pricing under market frictions

We assume that the time horizon is finite and discrete, indexed by $t = 0, 1, 2, \ldots, T$. Three types of assets, the stock, the risk-free bond, and European call and put options written on the stock, are traded in the market. We denote the stock price by S_t and its dividend payment at time t by D_t. The gross return of the stock is denoted by $R_{t,t+1}$ (i.e., $R_{t,t+1} = (S_{t+1} + D_{t+1})/S_t$). The gross risk-free rate from time t to $t+1$ is denoted by $R^0_{t,t+1}$. We assume that options written on the stock are one-period options (i.e., options traded at time t mature at $t+1$) and traded at a set of strikes $\mathcal{K}_t$. The time t call (put) option price with strike price $K \in \mathcal{K}_t$ is denoted by $C_t(K)$ ($P_t(K)$).

We assume that there exists an agent who participates in *both* the stock market and the option market. She sets their optimal consumption and asset allocations by maximizing her expected lifetime utility, yet her asset allocation is subject to constraints caused by market frictions. The assumption of the existence of such an agent is realistic and it is in line with recent literature; for example, large financial intermediaries trade in multiple financial markets including the stock market and the option market under market frictions, and a growing number of recent studies consider financial intermediaries to be the marginal investors (e.g., Adrian et al. (2014), He et al. (2017)).

Let θ^0_t, θ^S_t, $\theta^c_t(K)$ and $\theta^p_t(K)$ be the agent's position on the risk-free bond, the stock, the call and put options, respectively and let $\boldsymbol{\theta}_t$ be the vector of these thetas. The agent solves the following portfolio-consumption problem,

$$\max_{\{c_j, \boldsymbol{\theta}_j\}} \sum_{j=t}^{T} \beta^{j-t} \mathbb{E}^{\mathbb{P}}_t [u(c_j)], \tag{2}$$

where $\mathbb{E}_t^{\mathbb{P}}$ is the conditional expectation under the agent's subjective belief $\mathbb{P}$ given the information up to time t, β is the subjective discount factor, $u(c)$ is the time-separable utility function. The agent chooses a consumption stream $\{c_j\}_{j\geq t}$ and portfolio allocations $\{\boldsymbol{\theta}_t\}_{j\geq t}$ subject to the following conditions. First, the agent's wealth at time t, W_t, changes over time as follows:

$$W_{t+1} = \theta_t^0 R_{t,t+1}^0 + \theta_t^S(S_{t+1}+D_{t+1}) + \sum_{K\in\mathcal{K}_t}\left[\theta_t^c(K)(S_{t+1}-K)^+ + \theta_t^p(K)(K-S_{t+1})^+\right], \quad (3)$$

where $(x)^+ = \max(x,0)$. Second, the consumption at time t is given by

$$c_t = W_t - \theta_t^0 - \theta_t^S S_t - \sum_{K\in\mathcal{K}_t}\left[\theta_t^c(K)C_t(K) + \theta_t^p(K)P_t(K)\right]. \quad (4)$$

In equations (3) and (4), we normalize the price of the one-period bond at time t to unity and view $R_{t,t+1}^0$ as its payoff at time $t+1$. Third and most importantly, we formalize market frictions as constraints on the portfolio allocation of the agent. Even though we do not specify the types of frictions, we assume that there are L types of constraints on the portfolio allocation of the agent:

$$g_t^l(\boldsymbol{\theta}_t) \geq 0, \qquad l = 1,2,\ldots,L. \quad (5)$$

Let $V_t(W_t)$ be the time-t value function of the constrained maximization problem (2) subject to equations (3) to (5). Then, the Bellman equation is given by

$$V_t(W_t) = \max_{c_t,\boldsymbol{\theta}_t}\left\{u(c_t) + \beta\mathbb{E}_t^{\mathbb{P}}[V_{t+1}(W_{t+1})]\right\} \quad s.t. \quad \text{equations (3)–(5)}. \quad (6)$$

Given equations (3), (4) and the constraints in (5), the first-order condition of the Bellman equation (6) regarding the allocation to the stock θ_t^S yields

$$S_t = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1}+D_{t+1})] + M_t^S, \quad \textit{with} \quad M_t^S = \sum_{l=1}^{L}\frac{\lambda_t^l}{u'(c_t)}\frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial\theta_t^S}, \quad (7)$$

where $m_{t,t+1}^* = \beta V_{t+1}'(W_{t+1})/u'(c_t)$ is the intertemporal marginal rate of substitution (IMRS) between time t and $t+1$, and λ_t^l is the Lagrange multiplier of l-th constraint of equation (5).[6] The second term in the right-hand side of equation (7), M_t^S, captures the effect of market frictions on the market price of the stock. It can be interpreted economically as the nominal shadow cost of frictions incurred by their existence.[7] Equation (7) shows that the current stock price deviates from the IMRS-discounted expected future cum-dividend stock price in the case where some of the constraints are binding. Equivalently, equation (7) shows that the standard asset pricing formula $1 = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}]$, which holds in frictionless markets, does not hold. This result is also derived by He and Modest (1995). Option prices satisfy the analogous first-order conditions to equation (7):

$$C_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1} - K)^+] + M_t^c(K), \quad with \quad M_t^c(K) = \sum_{l=1}^{L} \frac{\lambda_t^l}{u'(c_t)} \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)}, \tag{8}$$

$$P_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(K - S_{t+1})^+] + M_t^p(K), \quad with \quad M_t^p(K) = \sum_{l=1}^{L} \frac{\lambda_t^l}{u'(c_t)} \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}. \tag{9}$$

In analogy to M_t^S in equation (7), $M_t^c(K)$ and $M_t^p(K)$ capture the effect of market frictions on the market call and put option prices, respectively.[8]

The following Theorem provides the asset pricing model under market frictions.

Theorem 2.1. *Under market frictions, the following asset pricing model holds:*

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}] - R_{t,t+1}^0 = CFER_{t,t+1} - \frac{Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1})}{\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*]}, \tag{10}$$

where $CFER_{t,t+1}$ is the contribution of frictions to the expected return from t to $t+1$,

[6]The value function V_t depends on t because we consider a finite horizon model, and the constraint functions g_t^l may also depend on time-varying parameters. Note also that the standard envelop condition $u'(c_t) = V_t'(W_t)$ does not necessarily hold in our model because g_t^l may depend on the agent's wealth.

[7] To exemplify this, consider the case of the margin cosntraint function $g_t^{MC}(\boldsymbol{\theta}_t) = W_t - |\theta_t^S|\mu_t^S S_t - \sum_{K\in\mathcal{K}}(|\theta_t^c(K)|\mu_t^c(K)C_t(K) + |\theta_t^p(K)|\mu_t^p(K)P_t(K))$, where μ_t^S, $\mu_t^c(K)$ and $\mu_t^p(K)$ are the margin rates of the stock, call option and put option, respectively. Then, $M_t^S = (\lambda_t^{MC}/u'(c_t)) \times sgn(-\theta_t^S)\mu_t^S$. The former term is the nominal shadow price of one unit of wealth pledgeable as margin and the latter part equals the amount of margin that needs to be posted for trading one unit of the stock. Note that the effect of market frictions on the stock price, M_t^S may depend on the agent's allocations to other assets, as well. For example, in the above margin constraint example, the value of M_t^S depends on whether the margin constraint is binding and hence it depends on the total amount of margins the agent needs to post, which is a function of the vector of allocations $\boldsymbol{\theta}_t$.

[8]Regarding the risk-free bond, to simplify the exposition, we assume that $\mathbb{E}_{t,t+1}^{\mathbb{P}}[m_{t,t+1}^*] = 1/R_{t,t+1}^0$ holds, which is equivalent to assuming that there is no effect of frictions on the risk-free bond market. In Appendix D, we extend the model to allow for a non-zero effect of frictions on the risk-free bond market. Then, we demonstrate that the effect of frictions on the risk-free rate has no impact on the results presented in the main body of the paper.

defined as

$$CFER_{t,t+1} = -R^0_{t,t+1}\frac{M^S_t}{S_t} = -\frac{R^0_{t,t+1}}{S_t}\sum_{l=1}^{L}\frac{\lambda^l_t}{u'(c_t)}\frac{\partial g^l(\boldsymbol{\theta}_t)}{\partial \theta^S_t}. \tag{11}$$

Proof. See Appendix A.1. □

Three remarks are in order at this point. First, equation (10) nests the standard frictionless market model. When no constraints are binding, equation (11) shows that $CFER_{t,t+1} = 0$ and thus equation (10) boils down to the standard asset pricing equation. In addition, equation (10) nests Gârleanu and Pedersen (2011) as a special case for the case where $L = 1$ and the constraint is the margin constraints. Then, $CFER_{t,t+1}$ becomes what they call the *alpha*, which is the product of the Lagrange multiplier of the margin constraints and the margin rate of the stock. Second, the decomposition of expected excess returns in equation (10) suggests that CFER does not represent compensation for risk. Instead, CFER is part of the expected excess return, which cannot be explained by the covariance risk premium term in the presence of frictions, where the covariance risk premium term is calculated as the covariance between the asset return and the IMRS. The CFER term appears because of the binding constraints on asset allocations as equation (11) shows. Third, the IMRS is affected by frictions, that is, $m^*_{t,t+1}$ depends on the agent's optimal asset positions $\boldsymbol{\theta}_t$, which are formed under frictions. However, $m^*_{t,t+1}$ does not subsume the full effect of frictions.

2.2 Estimation of CFER: The formula

Equation (11) shows that CFER is a function of the unobservable Lagrange multipliers. Hence, equation (11) cannot be used to estimate CFER unless further assumptions on the form of frictions and the IMRS are made. To circumvent these obstacles, we develop an option-based formula which enables us to proxy CFER without imposing assumptions on the IMRS nor on the types of market frictions; instead, the formula relates CFER to observable terms. To derive our formula, we proceed as follows. First, we assume that the dividend payment at $t + 1$, D_{t+1}, is deterministic given the information up to time

t. This assumption is plausible when the time length between t and $t+1$ is short (e.g., one-month as it will be the case in the subsequent empirical analysis) because the near future dividend payments are usually pre-announced. Second, we define the price of a synthetic stock $\widetilde{S}_t(K)$ as

$$\widetilde{S}_t(K) = C_t(K) - P_t(K) + \frac{K + D_{t+1}}{R^0_{t,t+1}}. \tag{12}$$

This combination of long call, short put and risk-free bond position is called a synthetic stock because it has the same payoff at time $t+1$ as the underlying stock, $S_{t+1} + D_{t+1}$.

Theorem 2.2. *Assume that D_{t+1} is deterministic given the information up to time t. Then, for any strike K, CFER is decomposed as*

$$CFER_{t,t+1} = CFER^{MF}_{t,t+1}(K) + U_{t,t+1}(K), \tag{13}$$

where

$$CFER^{MF}_{t,t+1}(K) = \frac{R^0_{t,t+1}}{S_t}(\widetilde{S}_t(K) - S_t) \tag{14}$$

is a scaled deviation from put-call parity between the stock price S_t and the synthetic stock price $\widetilde{S}_t(K)$.[9] *The second term $U_{t,t+1}(K)$ in equation (13) is given by*

$$U_{t,t+1}(K) = -\frac{R^0_{t,t+1}}{S_t}[M^c_t(K) - M^p_t(K)], \tag{15}$$

where $M^c_t(K)$ and $M^p_t(K)$ are defined in equations (8) and (9).

Proof. The proof of Theorem 2.2 relies on the idea that deviations from put-call parity, $S_t - \widetilde{S}_t(K)$, is a function of the effect of market frictions on the options' and the underlying stock's prices. To see this, under the conditionally deterministic dividend payment assumption, substitution of equations (8) and (9) into equation (12) yields the synthetic stock price as

$$\widetilde{S}_t(K) = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1} + D_{t+1})] + (M^c_t(K) - M^p_t(K)). \tag{16}$$

[9]The superscript MF of $CFER^{MF}$ stands for "model-free" because equation (14) can be calculated from data without estimating parameters.

Since the first term in the right hand side of equations (7) and (16) are the same, deviations from put-call parity equal

$$S_t - \widetilde{S}_t(K) = M_t^S - (M_t^c(K) - M_t^p(K)), \tag{17}$$

that is, the difference between the effect of market frictions on the underlying stock M_t^S and those on the synthetic stock $M_t^c(K) - M_t^p(K)$. Then, by scaling equation (17) by $-R^0_{t,t+1}/S_t$, we obtain

$$CFER^{MF}_{t,t+1}(K) = CFER_{t,t+1} - U_{t,t+1}(K) \tag{18}$$

given equations (11), (14), and (15). This proves equation (13). □

Theorem 2.2 shows that the stock's CFER is the sum of the scaled deviation from put-call parity $CFER^{MF}_{t,t+1}(K)$ which can be computed from market option prices as long as a pair of European call and put options with the same maturity and strike is available, and the unobservable term $U_{t,t+1}(K)$, which is a function of the effect of market frictions on option prices, $M_t^c(K)$ and $M_t^p(K)$ (see equations (8) and (9)). Given that $CFER_{t,t+1}$ is a function of the effect of frictions on the underlying M_t^S (equation (11)), the $U_t(K)$ term originates from the fact that deviations from put-call parity are determined by both the effect of market frictions on the underlying stock price M_t^S and also on the synthetic stock price $M_t^c(K) - M_t^p(K)$ (equations (17) and (18)). Subsequently, we show that we can estimate CFER reliably by using only the model-free observable part $CFER^{MF}_{t,t+1}(K)$. In particular, we estimate $U_{t,t+1}(K)$ by examining three alternative models of the effect of market frictions on option prices (i.e., models for M_t^c and M_t^p) and we find that the magnitude of $U_{t,t+1}(K)$ is of second-order importance compared to $CFER^{MF}_{t,t+1}(K)$. We discuss this issue in detail in Section 3.3.

Equation (17) echoes equation (29) of Gârleanu and Pedersen (2011), which shows that a deviation from the law of one price is a function of market frictions (i.e., the Lagrange multipliers term), and it does not depend on the preference nor the subjective beliefs. As a result, our CFER formula requires no assumptions on the preferences (IMRS

m^*) and subjective beliefs ($\mathbb{P}$).

Four more remarks are in order regarding the use of $CFER^{MF}_{t,t+1}(K)$ as a proxy of CFER. First, the "scaling coefficient" $R^0_{t,t+1}/S_t$ of $CFER^{MF}_{t,t+1}(K)$ converts the deviation in *prices* $(\widetilde{S}_t(K) - S_t)$ to a return metric, hence making CFER a *quantitative* measure of the effect of market frictions on expected stock *returns*.[10] Second, deviations from put-call parity are equivalent to a non-zero implied volatility spread (IVS, Cremers and Weinbaum (2010)). In line with this, in Section 5 we show that $CFER^{MF}_{t,t+1}(K)$ can be approximated using IVS.

Third, the scaled deviations from put-call parity, $CFER^{MF}_{t,t+1}$, proxy the part of expected *return*, which is not explained by the covariance risk premium. On the other hand, deviations from put-call parity should not be interpreted as a measure of the current level of mispricing in the underlying stock price, or equivalently, the synthetic stock price should not be interpreted as a measure of the "fundamental" price. Indeed, the synthetic stock price is "contaminated" by the effect of frictions even when $M^c_t(K) - M^p_t(K)$ is zero; the synthetic stock price equals the expected IMRS-discounted value of the payoff at time $t+1$, $S_{t+1} + D_{t+1}$, where S_{t+1} is affected by the market frictions (this can be seen by considering equation (7) for time $t+1$).

Fourth, the fact that we do not specify the number and types of frictions makes us agnostic about what are the actual market frictions which affect the returns of optionable stocks. This approach is similar to Brennan and Wang (2010) and Hou et al. (2016), who investigate how mispricing or frictions contribute to stock returns based on a reduced form model of mispricing and market frictions, respectively. Moreover, we take a reverse engineering approach to study the effect of market frictions on stock returns. Rather than first postulating the possible types of frictions and then measure their effect on asset returns, we estimate CFER first and then we examine how it covaries with various proxies of market frictions. This will reveal the type of frictions which predominantly

[10]Indeed, $CFER^{MF}_{t,t+1}(K)$ can be rewritten as $CFER^{MF}_{t,t+1}(K) = R^0_{t,t+1}(\widetilde{S}_t(K)/S_t - 1)$. Then, dividing equation (16) by S_t yields the relation $\widetilde{S}_t(K)/S_t = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R_{t,t+1}] - U_{t,t+1}(K)/R^0_{t,t+1}$, that is, the ratio of the two stock prices $\widetilde{S}_t(K)/S_t$ is a function of the underlying stock return.

give rise to CFER. This reverse approach is robust because it is founded theoretically. CFER measures the overall effect of market frictions on expected returns by circumventing model mis-specification concerns. In addition, CFER arises due to market frictions and hence various types of frictions should covary with it. Our subsequent empirical analysis confirms that the estimated CFER covaries with some know types of frictions such as transaction costs, short-sale constraints, and stock level and market level liquidity.

2.3 Properties of CFER and testable hypotheses

Our CFER formula allows us to study the properties of CFER dictated by theory. Our asset pricing model yields three testable hypotheses regarding the relation between CFER, expected asset returns and frictions.

HYPOTHESIS 1. *The asset's expected return is increasing with CFER.*

Equation (10) shows that the greater CFER is, the greater the asset's expected return. Hence, we expect that when we sort stocks in portfolios based on their respective estimated CFER, the post-ranking portfolios' average return and CFER will be positively related and a long-short spread portfolio should earn a positive average return and alpha.

HYPOTHESIS 2. *In the case where the IMRS m^* is described by a linear combination of risk factors, then the regression of the* CFER-adjusted excess return, $R_{t,t+1} - R^0_{t,t+1} - CFER_{t,t+1}$ *on the risk factors should yield a zero intercept.*

In the case where the IMRS m^* is described by a linear combination of risk factors $\boldsymbol{f}$, then our asset pricing equation (10) implies that

$$\mathbb{E}^{\mathbb{P}}_t[R_{t,t+1}] - R^0_{t,t+1} - CFER_{t,t+1} = \boldsymbol{\beta}'_R \mathbb{E}^{\mathbb{P}}_t[\boldsymbol{f}_{t+1}], \tag{19}$$

where $\boldsymbol{\beta}_R$ is the vector of the factor betas. Next, let us consider the following regression model:

$$R_{t,t+1} - R^0_{t,t+1} - CFER_{t,t+1} = \alpha + \boldsymbol{\beta}'\boldsymbol{f}_{t+1} + \varepsilon_{t+1}. \tag{20}$$

Then, the intercept α of equation (20) should be zero under the second hypothesis. This theoretical result is a generalization of the expected return-beta representation theorem from the case of frictionless markets (Cochrane (2005), Chapter 12.1) to the case where market frictions and hence a non-zero CFER exist. Failing to reject the null hypothesis of a zero intercept confirms one of the testable implications of our model.[11]

HYPOTHESIS 3. *Higher transaction costs imply a wider range of CFER values.*

Hypothesis 3 is about the relation between CFER and transaction costs. To prove this hypothesis, we follow He and Modest (1995) and assume that there is a proportional transaction cost $\rho > 0$ (i.e., ρS_t is charged as transaction costs when traders buy or sell the stock); without the loss of generality, no other types of frictions are assumed. Then, under our asset pricing model, the following Proposition holds.

Proposition 2.1. *The following expression holds:*

$$-\frac{2\rho}{1+\rho}R^0_{t,t+1} \leq CFER_{t,t+1} \leq \frac{2\rho}{1-\rho}R^0_{t,t+1}. \tag{21}$$

Proof. See Appendix A.2. □

Proposition 2.1 yields the third testable implication: stocks which exhibit higher transaction costs may take more extreme CFER values (either very negative or very positive). Equation (21) shows that the range of CFER values should be approximately equal to twice the round-trip transaction costs (4ρ). Given that theoretically CFER is a function of market frictions, it is not surprising that the range of CFER is confined by transaction costs, which is a type of market frictions. Moreover, equation (21) implies a theoretical upper bound of the alpha of the CFER-sorted spread portfolio; CFER has also an alpha interpretation because it is the part of the expected return which cannot be explained by the covariance risk premium. The theoretical range of CFER suggests that the upper bound of the alpha of the spread portfolios should be approximately twice

[11] Note that a zero intercept is a necessary but not a sufficient condition for asset pricing models to be valid. The latter would require testing whether the factors are priced something which is beyond the scope of this paper since our focus is not on testing asset pricing models.

the round-trip transaction costs. In Sections 3.4 and 4.1, we assume plausible values of ρ for the average stock of our sample, and confirm the consistency of our empirical CFER estimates and alphas with the theoretically predicted ones.

We will test the hypothesis implied by Proposition 2.1 via three alternative routes. First, we will eyeball the times-series evolution of the CFER's variation and discuss it in the light of major market events. We expect that the more distressed the market is, the greater the CFER's variation will be. Second, we will examine the relation of CFER with firms' and stocks' characteristics; this will be done by sorting stocks in portfolios according to their CFER values. We expect that the portfolios in which CFER takes extreme values are subject to greater frictions. Third, we will investigate the performance of spread portfolios formed by dependent bivariate sorting exercises. In particular, we will first sort stocks in portfolios by their respective proxy for transaction costs. Then, within any given portfolio, we will sort stocks in portfolios based on their respective CFER and calculate the spread portfolios' returns. We expect that the average return of the spread portfolios will increase as a function of the transaction costs proxy. This is because the higher transaction costs are, the more extreme CFER will be and hence the greater the expected return of the spread portfolios due to Hypothesis 1. We examine these conjectures in Sections 3.4 and 4.3.

3 Data and CFER estimation

3.1 Data sources

We obtain end-of-month U.S. equity option prices and implied volatilities (IVs) from the OptionMetrics Ivy DB database (OM) via the Wharton Research Data Services. Our dataset spans January 1996 to April 2016 (244 months). Options written on the U.S. individual equities are American style. OM calculates IVs via the Cox et al. (1979) binomial tree model, which takes the early exercise premium of American options into account. Given that our formula to estimate CFER (Theorem 2.2) relies on European option prices, we convert OM-IVs to the corresponding European option prices via the Black and Scholes (1973) option pricing formula.[12] We also obtain the risk-free rate and dividend payment data from the OM database to calculate the present value of dividend payments over the option's life time. We remove IVs if the recorded corresponding option bid price is non-positive, the IV is missing, and the option's open interest is non-positive. We discard data with time to maturity shorter than 8 days or longer than 270 days. We keep option data only when the moneyness K/S_t is between 0.9 and 1.1 to ensure that the most liquid option contracts are considered.

We obtain stock returns from the Center for Research in Security prices (CRSP). In line with the literature, our stock universe consists of all U.S. common stocks (CRSP share codes 10 and 11). We obtain the time-series of risk factors in the CAPM, Fama and French (1993) 3-factor model (FF3), Carhart (1997) 4-factor model (FFC), and Fama and French (2015) 5-factor model (FF5) from Kenneth French's website. We obtain the factors in the Stambaugh and Yuan (2017) mispricing factor model (SY) from Yu Yuan's website. We construct various firms' and stocks' characteristics variables (e.g., size, book-to-market, bid-ask spread) based on CRSP and Compustat database. For the definition and the data source of the various characteristics variables, see Appendix B.

3.2 Estimation of CFER: Choice of strikes and maturities

We estimate stocks' CFER as the model-free observable term $CFER_t^{MF}$ in equation (13) with European option prices converted from OM-IV as described in Section 3.1. Specifically, we first calculate $CFER_t^{MF}(K,T)$ for any available strikes K and maturities T, at which both the call IV and put IV are available. The value of $CFER_t^{MF}(K,T)$ generally differs across different strikes and maturities and we deal with the choice of K and T as follows.

Regarding the choice of K, on each end-of-month date t and for each traded option

[12]This approach is often taken in the literature (see e.g., Martin and Wagner (2018)).

maturity T, we take the weighted average of $CFER_t^{MF}(K,T)$ to define AVE CFER as

$$CFER_t^{AVE}(T) = \sum_{K \in \mathcal{K}} \omega(K)\, CFER_t^{MF}(K,T), \tag{22}$$

where $\mathcal{K}$ is a set of strike prices with valid call IV and put IV and $\omega(K)$ is a weight. We follow the previous literature on option implied measures to use the open interest of the corresponding options as the weight (e.g., Cremers and Weinbaum (2010)). This weighted average procedure is in line with the literature to reduce possible measurement errors in the options data. As a robustness check, we also compute the forward-at-the-money (ATM) CFER for a given maturity T, defined as $CFER_t^{ATM}(T) = CFER_t^{MF}(K^*,T)$, where K^* is the traded strike price closest to the "forward price" $f_{t,T} = R^0_{t,T}(S_t - PVD_{t,T})$ and $PVD_{t,T}$ is the present value of dividend payments during $[t+1, T]$.

Regarding the choice of the options' maturity, we proceed as follows. In the subsequent empirical analysis, we will conduct monthly frequency portfolio analysis, where at the end of each month, we sort stocks based on the estimated CFER and we will examine certain properties of the post-ranking monthly returns. Therefore, the horizon of the estimated CFER should correspond to the horizon of expected returns. To this end, first we multiply each estimated CFER by $30/dtm$, where dtm denotes days-to-maturity. Then, we construct the 30-day constant maturity CFER (CM CFER) by linearly interpolating the two traded maturities surrounding the 30-day maturity. Note that a similar interpolation is employed in the CBOE's calculation of the VIX index, which represents the model-free implied volatility over the next 30 days. The estimated CFER is treated as missing if the 30-day maturity is not bracketed by two traded maturities. As a robustness check, we also use the estimated CFER from the closest to 30-days to-maturity options (CLS CFER) as an alternative to the CM CFER. It is expected that the CLS CFER becomes noisy as a predictor of the future monthly stock return when the closest to the 30-day traded maturity is distant from the 30-days to maturity target. To minimize this risk, we calculate this proxy only when the closest options' maturity is between 15-day and 45-day, otherwise we treat CFER as missing.

In sum, we have two ways to estimate CFER at each maturity, averaged across strikes (AVE) versus closest to forward-ATM (ATM), and two ways on the choice of maturities, linearly interpolated 30-day constant maturity CFER (CM) versus closest to 30-day (CLS). Thus, there are in total four corresponding cases to analyze labeled, AVE-CM CFER, ATM-CM CFER, AVE-CLS CFER, and ATM-CLS CFER, respectively. We use the AVE-CM CFER as the baseline estimated CFER for the purposes of our subsequent analysis, yet this is highly correlated with the other three CFER measures.

3.3 The unobservable term in the CFER formula: Discussion

Given that we estimate CFER using only the model-free observable term $CFER_{t,t+1}^{MF}$, these estimates may contain a bias due to ignoring the $U_{t,t+1}$ term (see equation (13)). To address this issue, we estimate the order of magnitude of this possible bias for the case of our baseline AVE-CM CFER. Note that the bias in AVE-CM CFER, which we denote by $\overline{U}_{t,t+1}$ is an average of the bias term $U_{t,t+1}(K)$ for each pair of call and put options across different strikes and maturities we use to calculate AVE-CM CFER.

To quantify the size of $\overline{U}_{t,t+1}$, we model the effect of frictions on option prices, $M_t^c(K)$ and $M_t^p(K)$ (and hence $U_{t,t+1}(K)$, see equation (15)), in three different ways based on the previous literature on the effect of measurement errors and market frictions on option prices and option returns. First, we regard $M_t^c(K)$ and $M_t^p(K)$ as measurement errors and we assume that they are independently and identically distributed with zero mean as in Bliss and Panigirtzoglou (2002) and Dennis and Mayhew (2009). Next, we consider the so-called *embedded leverage* effect documented by Frazzini and Pedersen (2012). They theoretically and empirically show that options with high embedded leverage attract investors who are subject to leverage constraints and hence these options have lower returns. Their finding suggests that leverage constraints affect option prices (i.e., non-zero $M_t^c(K)$ and $M_t^p(K)$ arise) and hence this may yield a non-zero $U_{t,t+1}(K)$. Finally, we quantify $M_t^c(K)$ and $M_t^p(K)$ based on the margin constraints model analyzed in Hitzemann et al. (2017). Santa-Clara and Saretto (2009) and Hitzemann et al. (2017)

document that margin constraints affect option returns and hence they may also yield a non-zero $U_{t,t+1}(K)$.

In Appendix C, we provide the details. Two are the main findings from our analysis in Appendix C. First, the distribution of $\overline{U}_{t,t+1}$ is fairly symmetric around zero for all three cases we examine. This suggests that the model-free proxy of CFER is on average accurate. Second, the magnitude of $\overline{U}_{t,t+1}$ is small for all three cases. For the first case, we show that the magnitude of $\overline{U}_{t,t+1}$ is less than 6.5 bps with probability greater than 90%. This magnitude is less than one thirtieth of the width of the 5th to 95th percentile range of AVE-CM CFER, which is estimated based on the observable model-free term $CFER^{MF}_{t,t+1}$, and hence it can be viewed as being negligible. For the latter two cases, we directly estimate $U_{t,t+1}(K)$ for each pair of call and put options based on either the embedded leverage model or the margin constraints model. Then, we construct a "fully-estimated" CFER as $CFER^{MF}_{t,t+1}(K) + U_{t,t+1}(K)$ and take the average across available strikes and maturities to construct the "fully-estimated" AVE-CM CFER.[13] We find that the baseline model-free AVE-CM CFER and the fully-estimated AVE-CM CFER are almost perfectly correlated (correlation above 0.96) for both the embedded leverage and the margin constraints models. We also find that the results on the cross-sectional predictive power of each one of these two fully-estimated CFER as a sorting variable (i.e., Hypothesis 1) is statistically indifferent from that of the baseline model-free CFER; there are no statistically significant differences between the alphas of the zero-cost spread portfolio of stocks formed by sorting stocks based on the baseline model-free AVE-CM CFER and each one of the fully-estimated AVE-CM CFER, respectively. These results suggest that any bias in the model-free AVE-CM CFER caused by ignoring $\overline{U}_t$ is negligible. In other words, the model-free AVE-CM CFER estimates the effect of frictions on stock's expected return accurately.

Our findings suggest that market frictions have a negligible effect on $\overline{U}_t$. This should not be interpreted as evidence that the option market is frictionless, though. In fact,

[13] Note that the fully-estimated CFER is no longer model-free, because the assumption on the form of market frictions is necessary to estimate the U_t term.

our finding does not contradict the previous empirical evidence that market frictions affect option returns (Santa-Clara and Saretto (2009), Frazzini and Pedersen (2012), Hitzemann et al. (2017)). This becomes evident by considering the factors which affect the magnitude of $U_t(K)$; it may be small because of the following two reasons. First, it becomes small if $M_t^c(K)/S_t$ and $M_t^p(K)/S_t$ are small. Indeed, empirically, these ratios are much smaller than the ratios $M_t^c(K)/C_t(K)$ and $M_t^p(K)/P(K)$; the latter ratios are the ones which measure the effect of frictions on option returns (one can show this by transforming equations (8) and (9)). Second, $U_{t,t+1}(K)$ is determined by the difference between $M_t^c(K)$ and $M_t^p(K)$ and therefore $U_{t,t+1}(K)$ will be small if $M_t^c(K)$ and $M_t^p(K)$ have the same sign and similar sizes; in this case, they will offset each other to some extent. In Appendix C.4, we provide a detailed discussion.

3.4 CFER: Summary statistics

Table 1, Panel A, reports the summary statistics of the estimated CFER at the end of each month for each one of the four ways of estimating CFER. We can see that there are about 333,000 stock-month CFER observations for the case of the AVE-CM and ATM-CM CFER, whereas this number increases to about 347,000 observations for the case of the AVE-CLS and ATM-CLS CFER. This yields on average about 1,370 (1,420) stocks in each month in the case of AVE-/ATM-CM CFER (AVE-/ATM-CLS CFER) given that there are 244 months in our sample. This is a sufficient number to form well diversified decile portfolios in the subsequent analysis. The mean and the median of the estimated CFER are about -0.1% and -0.04% per month (30-day), respectively. Results are similar across the four construction methods of CFER. The distribution of CFER is skewed to the left and it is highly leptokurtic. The estimated CFER is sizable; it takes both positive and negative values, ranging from -1.24% to 0.89 % per month (-14% to 11% per year) in a 5th to 95th percentile range of AVE-CM CFER. Note that this range is consistent with the theoretically derived CFER bounds as a function of transaction costs, equation (21). Lesmond et al. (1999) and Hasbrouck (2009) document that the round-trip transaction costs (i.e., 2ρ in equation (21)) for large stocks are in the order of 1.0%. Hence, equation (21) predicts that the lower and upper CFER bound will be around -1% and 1% per month, respectively (the gross risk-free rate is about 20 basis points on average during our sample period).

CFER also has fairly large variations; the standard deviation is about 1% and the interquartile range (IQR, the difference between 75th and 25th percentile points) is between 47–60 bps on average across stocks over time depending on the CFER construction method. This magnitude of variation is relatively large compared to the long-run average U.S. equity risk premium, which is about 50 bps per month (or 6% per year, see e.g., Mehra (2012)). The percentage of the negative observations of CFER is about 55% in any of the four construction ways of CFER; CFER takes more often negative than positive values over the full sample period. Table 1, Panel B, reports that the four ways of computing CFER are almost perfectly correlated. Therefore, the subsequent analysis is expected to be robust to the choice of the method to estimate the 30-day CFER.

[Table 1 about here.]

Figure 1a shows the time-series evolution of the monthly median of AVE-CM CFER. This takes mostly negative values until the recent financial crisis. A negative median CFER implies that there are more stocks with negative than positive CFER (the proportion of negative CFER is around 62% until 2006). This observation is consistent with Ofek et al. (2004), who study deviations from put-call parity from July 1999 to November 2001. They find that the underlying stock prices is greater than the synthetic stock prices (i.e., negative CFER, see equation (13)) in two thirds of their sample. This is very close to our result of 63% of negative CFER during the same period (i.e., 1999 to 2001). However, after the financial crisis, the median of the estimated CFER takes both positive and negative values and its variability has increased.

[Figure 1 about here.]

Figure 1b shows the time-series evolution of the monthly IQR of AVE-CM CFER. We measure the dispersion of the estimated CFER by using this statistic rather than the standard deviation because the distribution of CFER is highly skewed and leptokurtic. As we have discussed in Section 2.3, the degree of the dispersion in CFER is determined by the size of transaction costs and hence by the degree of market frictions (Hypothesis 3). The time-series fluctuations in the IQR are in line with this predictions: most of the spikes in the IQR correspond to market turmoils, such as Russian default and LTCM crisis (August to September 1998), the collapse of Lehman Brothers and ensuing market meltdown (September to November 2008), European debt crisis (November 2011, uncertainty was the highest around the general election in Greece), and the Chinese stock market turmoils (June 2015 to January 2016).[14]

Finally, note that the calculation of CFER requires option price data. As a result, our universe of stocks is confined to the optionable stocks (i.e., stocks which have options written on them). However, this should not be viewed as a shortcoming of this study. In line with the results of Cremers and Weinbaum (2010), our optionable stocks are big stocks; the average market capitalization of stocks with (without) AVE-CM CFER is about 9.1 billion (0.5 billion) U.S. dollars over our sample period from 1996 to 2016. Relatedly, albeit we can estimate AVE-CM CFER for about 27% of stocks (about 1,350 optionable stocks out of 5,000 all common stocks in each month), these stocks on average account for about 90% of the aggregate market capitalization of U.S. common stocks over our sample period. In addition, even though our cross-section of U.S. optionable stocks is subject to smaller frictions compared to the non-optionable stock universe, still the CFER values as well as the effect of market frictions on expected returns is sizable as reported and we will further demonstrate in Section 4.[15]

[14] This is in line with the literature that the degree of market frictions intensify during market distress periods. Gârleanu and Pedersen (2011) and Nagel (2012) find that the margin and liquidity constraints, respectively become tighter during market turmoil periods. Hou et al. (2016) find that their microstructural friction measure takes greater values during recessions and market distress periods.

[15] For example, the average Amihud's (2002) illiquidity measure of the optionable (non-optionable) stocks is 0.01 (5.28), and the average relative bid-ask spread of optionable (non-optionable) stocks is 0.48% (2.50%) over our sample period.

4 Testable predictions: Empirical evidence

In this section, we examine the testable predictions (Hypotheses 1, 2, and 3) of our CFER asset pricing model discussed in Section 2.3.

4.1 Predictive power of CFER for future returns

First, we test Hypothesis 1 that CFER predicts future stock returns; stocks with higher CFER should earn a higher expected return compared to stocks with a lower CFER. To this end, we examine whether CFER predicts equity returns cross-sectionally by taking a portfolio sorting approach. We sort stocks in decile portfolios by using the estimated CFER as a sorting criterion. Portfolio 1 (10) contains the stocks with the lowest (highest) CFER. We form portfolios at the end of each month. Then, we calculate the post-ranking monthly return of each portfolio and the zero-cost long-short spread portfolio, where we go long in Portfolio 10 and short in Portfolio 1. Our testable hypothesis suggests that this zero-cost long-short portfolio will earn a positive average return.

Table 2 reports the results for both the value-weighted and equally-weighted decile portfolios cases, where we use the AVE-CM CFER as a sorting variable. In line with the model's prediction, we can see that there is a monotonically increasing relation between the portfolios' average returns and CFER. Moreover, the average return of the long-short value-weighted spread portfolio is 1.64% per month. This value is sizable and statistically significant (t-stat: 5.77). We also calculate the risk-adjusted returns, in terms of alpha with respect to the CAPM and FFC model.[16] Both the CAPM- and FFC-alpha are sizable and statistically significant; α_{CAPM} is 1.70% and α_{FFC} is 1.86% per month and their t-statistics are above five which is above the threshold proposed by Harvey (2017) for the purposes of addressing data snooping concerns. These results show that the estimated CFER predicts future stock returns over and above other well known risk factors.

The order of magnitude of the estimated alphas for the spread portfolio is in accor-

[16] For all portfolio sort exercises in this Section, we also estimate alphas with respect to FF3, FF5, and SY models. Results are qualitatively similar and hence we do not report them due to space limitations.

dance with the alpha predicted by equation (21) once we set ρ equal to 0.5% in line with the empirical evidence on the transaction costs of big stocks. Equation (21) predicts that the bounds for alphas in the presence of frictions (i.e., CFER) of the long and short portfolios should be 1% and -1%, respectively. This amounts to an upper bound of alpha of 2% per month for the spread portfolio. This would explain the large alpha of the CFER-sorted spread portfolio; the limits of arbitrage for trading (even big optionable) stocks are large enough to generate a 2% alpha per month. Therefore, the alphas reported in Table 2 are not excessive given the degree of market frictions investors face.

The equally-weighted portfolio earns an even more significant average return compared to the value-weighted portfolio; the average return is 1.73% per month, α_{CAPM} and α_{FFC} are 1.76% and 1.81% per month, respectively and t-statistics are above nine. Even though the equally-weighted result is stronger than the value-weighted result, in the subsequent analysis, we focus on the value-weighted results for two reasons. First, a number of studies recommends the value-weighted portfolio construction over the equally-weighted construction.[17] Moreover, as the value-weighted construction tends to result in lower alphas and t-statistics, our judgment on the predictive ability of CFER will be more conservative and hence even more credible.

Interestingly, our results suggest that the use of the model-free estimated CFER as a predictor of the cross-section of stock returns yields significant alphas even though our universe of optionable stocks corresponds to big stocks; Hou et al. (2017) document that the alphas found in a number of asset pricing studies become insignificant once small stocks are weighted less in the universe of test portfolios.

[Table 2 about here.]

[17]For example, Hou et al. (2017) recommend the value-weighted portfolio construction because equally-weighted portfolios exaggerate anomalies in microcap stocks, which are difficult to exploit in practice due to high transaction costs and illiquidity. Asparouhova et al. (2013) find that microstructure frictions can bias upward the cross-sectional monthly mean of equally-weighted returns. Based on a similar reasoning, Bali et al. (2016) state that "value-weighting is most appropriate when the entities in the analysis are stocks" (Bali et al. (2016)), footnote 1, Chapter 5).

4.2 Alpha of the CFER-adjusted excess returns

Next, we examine our second hypothesis. This hypothesis is about a test of linear factor model under market frictions (i.e., non-zero CFER). Especially, the left hand side of the regression of equation (20) should be the "CFER-adjusted return," $R - R^0 - CFER$.

Table 3, Panel A, reports the intercepts of the CFER-adjusted regressions, equations (20), where we regress the CFER-adjusted excess returns of the CFER-sorted value-weighted decile portfolios and the spread portfolio on a set of factors $\boldsymbol{f}$. We examine five models (CAPM, FF3, FFC, FF5, SY). We can see that the intercept of the regression is statistically insignificant at a 5% significance level whenever a decile portfolio return is used as a dependent variable. An exception occurs in the case where the spread portfolio return is used for the case where we use the CAPM to proxy the covariance risk premium. Moreover, Gibbons et al. (1989) (GRS) test (untabulated) does not reject the null hypothesis that all eleven alphas are jointly insignificant for any one of the five models examined even at a 10% significance level.

We repeat our analysis by discarding CFER values below 1st percentile point or above 99th percentile point of the CFER distribution across all stocks. Then, we sort stocks by the estimated CFER. This approach removes possible outliers in the estimated CFER; the possible outliers of the estimated CFER may affect the value of the CFER-adjusted returns and hence the estimated alphas. This data cleaning procedure is similar to the standard convention in the Fama and MacBeth (1973) regressions (see e.g., Bali et al. (2016)). Table 3, Panel B, reports the results. All intercepts now become insignificant at a 5% level. In Panel C, we conduct a further robustness test and report the result from a quintile portfolio sort analysis (without the previous truncation of the most extreme CFER values). A quintile portfolio sort is expected to be more robust to outliers because the formed portfolios contain more stocks and thus they are more diversified. We can see that the intercept is not statistically different from zero in all cases.

[Table 3 about here.]

Two remarks are in order regarding the results obtained from the CFER-adjusted regressions. First, the fact that we find insignificant alphas for all asset pricing models does not mean that all these models are valid. It simply verifies the testable hypothesis of our model. To make a statement about the validity of an asset pricing model, one should test whether the factors are priced, i.e., insignificant alpha is a necessary but not a sufficient condition about the validity of a model. Second, the insignificant alphas obtained from the analysis of the CFER-adjusted returns of the CFER-sorted portfolios imply that the large alphas obtained from the analysis of the *non*-CFER-adjusted expected returns of the CFER-sorted portfolios originate from market frictions as these are measured by the CFER term and they are not due to model mis-specification.

4.3 Relation between CFER and friction variables

Next, we provide two alternative ways to test Hypothesis 3 as discussed in Section 2.3. First, we examine the relation between the estimated CFER and various firms' and stocks' characteristics. Table 4 reports these characteristics for the CFER-sorted value-weighted decile portfolios, where we use the AVE-CM CFER as a sorting variable. Hypothesis 3 suggests that stocks with higher transaction costs are likely to exhibit more extreme CFER values. Our results confirm this conjecture. We can see U-shaped relations between the relative bid-ask spread (BAS), Amihud's (2002) illiquidity measure, stock price level, and the estimated CFER, that is, stocks with extreme estimated CFER values tend to have a wider bid-ask spread, greater illiquidity and lower stock prices.

There is an inverse U-shaped relation between CFER and the SIZE (the logarithm of the market equity). This is also consistent with Hypothesis 3; smaller size stocks are subject to larger market frictions and hence larger transaction costs (see e.g., Hasbrouck (2009) and Hou et al. (2016)). We also observe a U-shaped relation between the estimated CFER and the idiosyncratic volatility (IVOL) and the beta; stocks with extreme CFER value tend to have larger idiosyncratic risk and systemic risk. These relations are again consistent with Hypothesis 3 because a higher IVOL can be interpreted as an increase in the market friction in the sense that the higher riskiness of a stock discourages traders to trade the stock (see e.g., Stambaugh et al. (2015)). We also see that there is a U-shaped relation between CFER and variables which proxy short-sale constraints, that is, the relative short interest (RSI) (see Asquith et al. (2005)), and the estimated shorting fee (ESF) of Boehme et al. (2006). This may seem to be at odds with the literature, which documents that tight short-sale constraints are related to future underperformance (i.e., negative CFER); this implies that CFER should be monotonically (negatively) related with the size of short-sale frictions. However, our result may be driven by the correlation between RSI/ESF and other characteristics, which univariate sorts cannot take into account. Subsequently, we shed light on this relation by running Fama and MacBeth (1973) (FM) regressions, where we control for other characteristic variables such as firm size and liquidity. Finally, we also find a U-shaped relation between the book-to-market ratio (B/M) and the estimated CFER.

[Table 4 about here.]

Second, we examine Hypothesis 3 by conducting dependent bivariate sorts as discussed in Section 2.3; the variation of CFER will be greater within a group of stocks that is subject to larger transaction costs. The CFER-spread portfolio formed from stocks with larger CFER variation is expected to earn a higher average return because larger CFER variation means that the expected relative outperformance (underperformance) of the stocks in the long (short) leg is more pronounced. Therefore, in the case where we sort stocks first by a transaction costs-related variable and then by the estimated CFER, the CFER-spread portfolios' average returns will be higher for the bin of stocks which have the higher transaction costs. To confirm this conjecture, we conduct bivariate dependent sorts first by a transaction cost-related variable, then by the estimated CFER. Table 5, Panel A, reports the bivariate dependent sort, first by BAS, then by CFER. The result verifies our conjecture. The average CFER of the CFER-sorted spread portfolio increases with the level of the bid-ask spread. The average return and α_{FFC} of the CFER-sorted spread portfolios also increase with the level of the bid-ask spread. We find a similar pattern in the CFER-sorted portfolios in Table 5, Panel B, where we use the SIZE as an alternative sorting proxy for transaction costs. In general, the average CFER, average return, and α_{FFC} of the CFER-sorted spread portfolios decrease in the level of SIZE.[18]

[Table 5 about here.]

Finally, in addition to the portfolio sort approach, we also examine the relation between CFER and friction-related variables by conducting FM regressions. This constitutes a reverse engineering approach to identifying the dominant market frictions for optionable stocks; theoretically, CFER arises due to market frictions and hence it is expected to covary with them. To this end, we run univariate as well as multivariate regressions of CFER on SIZE, BAS, IVOL, Amihud's (2002) measure and RSI which are popular proxies of market frictions. For each month t ($t = 1, 2, ..., T$), we estimate the following cross-sectional regression across individual stocks indicated by i ($i = 1, 2, ..., n$):

$$CFER_{i,t,t+1} = \alpha + \beta' X_{i,t}, \tag{23}$$

where we use AVE-CM CFER as the left hand side variable and $X_{i,t}$ is a vector that contains the characteristics variables of individual stocks. Then, we calculate the time-series average and the t-statistics of the estimated T cross-sectional intercept α and the β coefficients. To ensure that our estimates are not driven by extreme values, we truncate AVE-CM CFER and variables in $X_{i,t}$ at a 1% threshold level.

Given that the previous analysis has documented a non-linear relation between CFER and firm characteristics, we conduct the regressions by splitting our CFER sample to positive and negative values. For the positive CFER subsample, our third hypothesis suggests that more extreme (i.e., higher) CFER corresponds to stocks which are subject to larger transaction costs and frictions. Therefore, we expect that the coefficient of SIZE is negative, and the coefficient of BAS, Amihud and IVOL are positive (smaller

[18] We obtain similar results which confirm our third hypothesis when we use idiosyncratic volatility, or Amihud's (2002) illiquidity measure as a proxy for transaction costs.

firms, wider bid-ask spread, lower liquidity and higher IVOL correspond to more extreme CFER). For the negative CFER subsample, we expect the opposite sign for the coefficients of these four variables. On the other hand, we expect that the coefficient of RSI will be always negative both for the positive and negative CFER subsamples, because higher RSI always implies severer short-sale constraints, which in turn implies lower CFER.

Table 6 reports the results. We can see that the coefficients of the SIZE, BAS, IVOL and Amihud variables have the expected signs both in the univariate and multivariate regressions. Moreover, they are statistically significant; the only exception is Amihud's measure for the positive CFER subsample. These findings corroborate that CFER is related to various liquidity- and transaction costs-related variables in the theoretically predicted manner. Regarding RSI, we obtain the expected negative sign in the multivariate regressions for both subsamples. This shows that, once controlling for other friction-related variables, RSI and CFER are negatively related as theory predicts. Note that the adjusted R^2 of the univariate regression of CFER on RSI is lower than those of the other friction-related variables. This may suggest that short-sale constraints are of second-order importance to explain CFER variations compared to the other friction-related variables for our universe of optionable stocks. This is expected because optionable stocks correspond to big stocks for which short-sale constraints are not pronounced (see e.g., D'Avolio (2002) and Drechsler and Drechsler (2014)). Most importantly, the documented relation between CFER and proxies of *various* market frictions suggests that CFER is a "sufficient statistic" which subsumes the overall effect of any relevant market frictions on expected stock returns.

[Table 6 about here.]

4.4 Robustness tests

In this subsection, we report a number of further robustness checks. We examine whether our baseline results may differ across the four possible ways of constructing CFER. We also investigate whether results are driven by outliers, stock reversals, non-synchronous trading in the option and underlying market. We also conduct FM regression tests to see whether CFER is related to stock returns.

First, we examine whether the average return and α_{FFC} of the decile spread portfolio differ across the four CFER proxies. Table 7, Panel A, reports the results. We can see that the average return and α_{FFC} are sizable and statistically significant in both the value-weighted and equally-weighted portfolios for any of the four ways of computing CFER. In addition, we can see that CFER computed by the AVE-CM method delivers the highest average return and alpha. This may be due to the fact that AVE-CM CFER reduces any measurement errors in CFER at each strike by averaging them and hence the signal to sort stocks in portfolios has greater predictive power. It may also be the case that the 30-day constant maturity CFER gives cleaner signals for future outperformance or underperformance in the succeeding month than the CFER extracted from options with maturity closest to 30-day does.

[Table 7 about here.]

Second, regarding the effect of extreme CFER values, we check whether the predictive power of CFER is driven by few stocks that have extreme CFER value. We perform two alternative robustness tests based on two respective ways of forming portfolios. First, we remove stocks whose CFER is below the 1st percentile point or above the 99th percentile point. Second, we form quintile rather than decile portfolios; each quintile portfolio has twice as many stocks compared to decile portfolios, portfolio returns are more robust to the effect of outliers. Table 7, Panel B, reports the average returns and alphas of the long-short portfolio. The first two columns report the average return and the risk-adjusted return of the decile spread portfolio, where we remove stocks whose CFER is below 1st percentile point or above 99th percentile point. We form two spread portfolios as the difference of Portfolio 10 minus Portfolio 1, and Portfolio 9 minus Portfolio 2, respectively. By construction, the latter spread portfolio contains stocks which have less extreme CFER values. We can see that albeit the average return and alpha decrease compared to the full sample results, results are still economically and statistically significant. The third and fourth column of Table 7 show the analogous results for the CFER-sorted quintile portfolios. Again, the average and risk-adjusted returns are economically and statistically significant. The results suggest that even though we use optionable stocks, their CFER values are not negligible. This is because we can construct a CFER spread portfolio with significant alphas even after we discard 40% of our initial sample with the most extreme CFER observations.

Third, the predictability of CFER may be a manifestation of the short-term reversal effect of Jegadeesh and Titman (1993), which is typically attributed to mispricing due to microstructural frictions (see Chapter 12 of Bali et al. (2016)). To examine this conjecture, we conduct a 5×5 dependent bivariate sort, where we first sort stocks according to the previous month return $R_{t-1,t}$, and then sort by the AVE-CM CFER. Hence, we can test whether CFER has predictive power after the previous month return is controlled. We report results in Table 8. The first five columns of Table 8 report the average returns of the 25 bivariate-sorted portfolios. The sixth to last columns report the average returns, α_{FFC}, and the average CFER of the long-short portfolios of CFER, respectively, after controlling the previous month returns. Overall, the spread portfolios' risk-adjusted returns (seventh column) are still statistically and economically significant after controlling the previous month return. This suggests that the predictive power of CFER is not subsumed by the short-term reversal phenomenon.

[Table 8 about here.]

Fourth, we examine whether our results on the documented predictive ability of CFER are of use to real time investors in the presence of non-synchronous trading in the option and the underlying stock market (Battalio and Schultz (2006)). The CBOE option market closes after the underlying stock market. Consequently, in real time, the CFER value computed from option closing prices may not be available to investors on the close of the stock market. As a result, in real time it may be the case that investors cannot exploit the

CFER signal since the stock market has closed and hence they cannot trade stocks.[19] In this case, inevitably, investors will trade stocks at the open of the next day. To examine whether the calculated at the end-of-day CFER may be of use to an investor, we calculate post-ranking returns using the open-to-close monthly stock return, where the open stock price is that of the first trading day after the day on which CFER is estimated.

Table 9, Panel A, reports the portfolio analysis results, where the open-to-close return is used. The average return of the spread portfolio is 1.60% per month and it is almost the same as the average return obtained from the baseline analysis using close-to-close returns, 1.64%. The FFC alpha is 1.83%, which is again almost the same as the corresponding alpha in the close-to-close return case, 1.86%. This result implies that the predictive power of the estimated CFER prevails even in the presence of non-synchronous trading in the stock and option market; the predictive power of CFER does not change overnight.

[Table 9 about here.]

Fifth, we examine whether results are robust in the case where we exclude stocks with low prices. Table 9, Panel B, reports the results, where we exclude stocks whose price level is lower than \$10. This filtering criteria removes about 10% of stocks compared to the baseline analysis. We can see that the average return and the alphas of the spread portfolio decrease when we remove the low priced stocks. However, the returns are still highly statistically and economically significant. This is in contrast with the literature on the predictability of friction-related variables, where the predictability mainly stems from small, low priced stocks which are more susceptible to market frictions.[20]

Sixth, we examine whether the predictive cross-sectional power of CFER prevails in the case where we use different breakpoints to form the decile portfolios. Table 9,

[19] The underlying market closes at 4:00 p.m. (EST). Prior to June 23, 1997, the closing time for CBOE options on individual stocks was 4:10 p.m. On June 23, 1997, CBOE changed the closing time to 4:02 p.m. (i.e., only two minutes after the closing of the underlying stock market). From March 5, 2008, OM reports option prices at 15:59 p.m. These changes minimize the potential non-synchronicity bias during our sample period. Nevertheless, in the absence of intra-day option prices, it is not known whether the CFER estimates were available in real time before the stock market close prior to March 5, 2008.

[20] For example, Hou et al. (2016) report that the predictive power of their FRIC measure, which captures the degree of microstructural frictions effect on expected return, decreases considerably when penny stocks (stock price $\leq$ \$1 or \$5) are excluded.

Panel C, reports the portfolio sort result, where we form decile portfolios based on the NYSE breakpoints. Hou et al. (2017) recommend using only NYSE stocks to compute breakpoints rather than using all stocks. This is because the latter method allows smaller and more volatile NASDAQ stocks to have a greater relative importance in the extreme decile portfolios and amplifies asset pricing anomalies. We can see that the predictive ability of CFER is robust irrespective to the breakpoint method. The average return and alpha of the spread portfolio are still significant, albeit smaller compared to these obtained in the baseline analysis.

A remark is in order at this point regarding the validity of our findings in the light of the growing concerns on data snooping among the asset pricing literature (e.g., Harvey et al. (2016), Hou et al. (2017), Harvey (2017)). Our results are reassuring because the CFER-sorted decile spread portfolio earns significant alphas even when we follow the construction method recommended by Hou et al. (2017) (i.e., value-weighted and NYSE breakpoints) and the t-statistics are above five, which is above the thresholds based on the Bayesianized t-statistics proposed by Harvey (2017). Furthermore, these recent studies emphasize the importance of relying on a sound theoretical model to explain why a certain variable should predict asset returns. Our approach satisfies this criterion since the predictive power of CFER is justified based on a formal asset pricing model. Moreover, these studies also emphasize that the design and practical specifications of empirical studies should not allow ad-hoc flexibility as possible. The computation of CFER allows little flexibility because it does not require any parameter estimations nor historical data. The only flexibility is in the choice of strike prices and maturities, yet we have shown that the predictive power of CFER is robust to the CFER construction methods (Table 7, Panel A).

Seventh, we examine whether the predictive power of CFER still exists over alternative sub-periods. We divide our initial sample period into January 1996 to December 2006 and January 2007 to April 2016. We choose December 2006 as a splitting point for the following two reasons: first, 2007 is the onset of the financial crisis and hence market frictions have increased in the period thereafter. This may have an effect on the cross-section of CFER values as Figures 1a and 1b have indicated. Second, 2007 coincides with the period where the academic research, which demonstrates that the option-implied measures extracted from individual equity options predict the cross-section of future stock returns, has appeared.[21] McLean and Pontiff (2016) find that the publication of academic research on asset pricing anomalies eliminates the predictability of variables which manifest asset pricing anomalies. Panels A and B of Table 10 report the results. The spread portfolio's average return and α_{FFC} decrease by 68 bps and 119 bps, respectively, from the earlier to the more recent sub-sample. However, the average return and alpha of the spread portfolio are still statistically and economically significant. These results show that the predictive power of CFER is not solely driven by financial crisis period.

[Table 10 about here.]

Finally, we complement the portfolio sorts with FM regressions, where we regress stock returns on stocks' characteristics including the estimated CFER. These regressions provide additional robustness checks for our results since they employ all firms without imposing portfolio breakpoints and allow for control variables (see Hou et al. (2016)). Similar to the estimation in Section 4.3, for each month, we estimate cross-sectional regressions of stock returns on characteristics variables of individual stocks. Then, we calculate the time-series average and the t-statistics of the estimated T cross-sectional intercept and the coefficients on characteristics variables. To ensure that our results are not driven by extreme values, we truncate left-hand side variables at a 1% threshold level.

Table 11 reports the result. Model (1) shows that the estimated CFER is positively related to the stock returns. In Model (2), we employ various control variables including market beta, SIZE, log of book-to-market ratio, momentum ($R_{t-12,t-1}$). We also include the previous month return $R_{t-1,t}$, IVOL, asset growth rate and profitability since it is well-known that these variables have predictive power for future stock returns (see e.g.,

[21] For instance, Cremers and Weinbaum (2010) and Bali and Hovakimian (2009) working paper versions appeared on the SSRN website in March 2007 and November 2007, respectively.

Jegadeesh and Titman (1993) for the short-term reversal, Ang et al. (2006) for IVOL, and Hou et al. (2015) for asset growth and profitability). The coefficient of the estimated CFER is still positive and statistically significant even after controlling for these variables.[22] In Model (3), we further add three liquidity related variables, Amihud's (2002) illiquidity measure, the relative bid-ask spread and the turnover rate. The estimated coefficient of CFER is virtually unchanged from Model (2).

In columns (4) to (9), we report results from conducting FM regressions on two separate sub-samples. First, as we have discussed above (Table 9, Panel C), NASDAQ stocks are smaller and more volatile than NYSE and Amex stocks. Hence, the FM regression results may be driven by the NASDAQ stocks (see Hou et al. (2016)). To examine this possibility, we repeat the FM regression by splitting our sample into NYSE/Amex stocks and NASDAQ stocks. Columns (4) and (5) report respective results. The coefficients of CFER are still highly significant regardless of whether we use only NYSE/Amex stocks or NASDAQ stocks. Next, as we have seen in Table 4, CFER and various firm and stock characteristics exhibit (inverse) U-shaped relations. Therefore, it might be the case that this non-linear structure affects the FM regression results. To address this issue, we split our initial sample based on the sign of CFER; we split our sample into two parts where the splitting points is a zero CFER value. Hence, the two parts roughly correspond to the left and right part of the U-shaped relations so that each subsample has a monotonic relation between CFER and the firm and stock characteristics. This would be closer to the structure of the FM regressions. Columns (6) and (7) demonstrate that the coefficient of CFER is larger for negative CFER samples, but the coefficient of CFER is significant for both subsamples. Finally, we split our sample into January 1996 to December 2006 and January 2007 to April 2016 as before and we re-apply the FM regressions. We can

[22] In our FM regression results, many traditional return predictors such as log book-to-market ratio and momentum are insignificant. To explore this further, we conduct FM regressions by excluding CFER from the set of control variables and using all common stocks including non-optionable stocks. In the case where our stock dataset commences in 1972, these traditional variables have significant coefficients, whereas if we use the data starting from 1996, they become insignificant. This suggests that well-known effects such as value and momentum effects are weaker in the recent period covered by the OM database. Therefore, the insignificant coefficients we obtain for some traditional variables should not be attributed to the narrower universe of optionable stocks neither on the inclusion of CFER in the regressions.

see from the last two columns that the estimated coefficient on CFER becomes slightly smaller in the latter period, but they are statistically significant in both sub-periods.

[Table 11 about here.]

5 Relation to other option-implied measures

In this Section, we discuss the relation of CFER with two measures of deviations from put-call parity, which have been documented to predict stock returns cross-sectionally: implied volatility spread (IVS) defined as the difference between the BS-IV of the call and put options with the same strike (e.g., Bali and Hovakimian (2009), Cremers and Weinbaum (2010)), and maturity and the DOTS measure of Goncalves-Pinto et al. (2017). In particular, we show that both IVS and DOTS are approximately proportional to $CFER^{MF}_{t,t+1}(K)$, which is the observable model-free part of CFER (equation (13)). We begin by providing the following Proposition which establishes the relation between CFER and IVS. Note that the following result is in line with the observation by Cremers and Weinbaum (2010) that a non-zero IVS reflects a violation of put-call parity.

Proposition 5.1. *Let $IV^c_t(K)$ and $IV^p_t(K)$ be the Black-Scholes call and put implied volatilities (BS-IVs), respectively. Then, the following approximate equation holds.*

$$CFER^{MF}_{t,t+1}(K) \approx \frac{R^0_{t,t+1}\mathcal{V}_t(K)}{S_t}(IV^c_t(K) - IV^p_t(K)), \tag{24}$$

where $\mathcal{V}_t(K)$ is the Black-Scholes vega evaluated at a strike K and a volatility equal to $(IV^c_t(K) + IV^p_t(K))/2$.

Proof. See Appendix A.3. □

Next, we show the relation between CFER and Goncalves-Pinto et al.'s (2017) DOTS measure. DOTS is calculated from a pair of American call and put option prices as

$$DOTS_t(K) := \frac{\frac{S^U_t(K)+S^L_t(K)}{2} - S_t}{S_t}, \tag{25}$$

where $S_t^U(K) = C_t^{ask}(K) - P_t^{bid}(K) + K + D_{t+1}/R_{t,t+1}^0$ and $S_t^L(K) = C_t^{bid}(K) - P_t^{ask}(K) + K/R_{t,t+1}^0$ are the no-arbitrage bounds for the stock price (i.e. $S_t^L \leq S_t \leq S_t^U$) calculated from the bid and ask prices of American call and put options (C^{bid}, P^{bid}, C^{ask}, and P^{ask}) with strike K. One can show that the mid-price of the American option-implied bounds S_t^U and S_t^L approximates a synthetic stock price. Therefore, as the following Proposition shows, the DOTS measure can be regarded as a function of deviations from put-call parity and hence as a function of $CFER^{MF}$.

Proposition 5.2. *Let η_t^c and η_t^p be the early exercise premium of the American call and put option, respectively. Then, the following relation holds:*

$$DOTS_t(K) = \frac{CFER_{t,t+1}^{MF}(K)}{R_{t,t+1}^0} + u_t, \quad u_t = \frac{1}{S_t}\left[\eta_t^c - \frac{D_{t+1}}{2R_{t,t+1}^0} - \left(\eta_t^p - \frac{K(R_{t,t+1}^0 - 1)}{2R_{t,t+1}^0}\right)\right]. \tag{26}$$

Proof. See Appendix A.4. □

Proposition 5.2 shows that DOTS is the discounted $CFER_{t,t+1}^{MF}(K)$ term plus an additional term u_t which is a function of the early exercise premium of the American call and put options.

Propositions 5.1 and 5.2 provide a theoretical explanation for the empirically documented predictive power of IVS and DOTS for future stock returns; they are approximately proportional to the observable part of CFER, $CFER_{t,t+1}^{MF}(K)$. Therefore, IVS and DOTS ought to predict future stock returns, too. Moreover, these results explain formally Goncalves-Pinto et al.'s (2017) finding that DOTS and IVS are highly correlated. However, the empirical performance of CFER versus IVS and DOTS as cross-sectional predictors of stock returns may differ since IVS and DOTS are approximations of $CFER_{t,t+1}^{MF}(K)$; the strength of the predictive power will depend on the size of the approximation error in equation (24) in the case of IVS and on the size of u_t in the case of DOTS. The predictive power of IVS itself also depends on the impact of omitting the vega scaling factor. DOTS is constructed from options which have different time-to-maturities which may not correspond to the 30-days return horizon and this may also incur biases.

In sum, our proxy of CFER, $CFER^{MF}$, is expected to perform at least as good as the other discussed option-implied measures in terms of predicting future stock returns. This is because our theoretical model suggests that our CFER formula is the most appropriate way to utilize the informational content embedded in deviations from put-call parity.

We compare the cross-sectional predictive ability of AVE-CM CFER to that of IVS and DOTS. We follow Bali and Hovakimian (2009) and calculate IVS by taking the average of the IVS of available pairs of call and put options across different strikes and maturities (see Appendix B for the detailed construction method of IVS). We construct DOTS in line with Goncalves-Pinto et al. (2017). Table 12 reports the average returns, and alphas for the spread portfolios formed on AVE-CM CFER, IVS and DOTS. We can see that the CFER-sorted spread portfolio earns greater alphas by 45–49 bps (27–42 bps) compared to the IVS-sorted (DOTS-sorted) portfolio. The difference between CFER and DOTS alphas is smaller than that between CFER and IVS. This result is expected because DOTS is not subject to the vega scaling point encountered in IVS, and the additional term in u_t in over our sample period is small.[23] In sum, in line with the previous literature and Propositions 5.1 and 5.2, both IVS and DOTS predict stock returns, and our proxy of CFER performs at least as good as these two measures.

[Table 12 about here.]

6 Conclusions and implications

We derive a formula to estimate the contribution of frictions to expected returns (CFER) within a formal asset pricing setting, and then we study empirically the theoretically founded properties of CFER. CFER is the part of the asset's expected return which is not explained by the covariance risk premium. We make no assumptions on the type of market frictions nor on investors' preference to derive the CFER formula. The formula relates CFER to the observable scaled deviations from put-call parity, thus formalizing

[23] We calculate u_t as $DOTS_t(K) - CFER^{MF}_{t,t+1}(K)/R^0_{t,t+1}$ and find that the monthly time series of the median of u_t is close to the half of the net risk-free rate, which is close to zero over our sample period.

the intuition and previous evidence that deviations from put-call parity are related to future stock returns. We show that the properly scaled deviations from put-call parity estimate CFER accurately. We also show theoretically that a number of measures of deviations from put-call parity such as the implied volatility spread proxy CFER.

We estimate CFER for each optionable U.S. common stock and we confirm the theoretically founded properties of CFER. Four are our main empirical findings. First, both the magnitude and variation in the estimated CFER is sizable. Second, CFER predicts future stock returns cross-sectionally; the predictive power of CFER is sizable and statistically significant (t-statistics exceed the value of five), and robust to the recent data snooping concerns. Third, the regressions of the CFER-adjusted excess returns (i.e., excess return minus the estimated CFER) of CFER-sorted decile portfolios on a set of standard risk factors yield non-significant intercepts for a number of asset pricing models. This suggests that the predictability of CFER originates from capturing the effect of market frictions, rather than from omitted risk factors. Fourth, we document that the cross-section of CFER becomes more dispersed when transaction costs and market frictions are larger and that CFER is related to a number of market frictions with transaction costs being the dominant one. This implies that CFER can be regarded as a sufficient statistic of the *overall* effect of market frictions on stock returns.

Three final remarks are in order. First, the empirical findings imply that even the expected returns of large stocks such as optionable stocks are considerably affected by market frictions. Second, we also document that the large alphas earned by the CFER-sorted portfolio are not "excessive" given typical estimates of transaction costs. The degree to which this alpha is exploitable in practice depends crucially on the type of investors and the degree of market constraints they face. Finally, even though CFER can be estimated only for optionable stocks (which tend to be large) and the period starting from 1996, our results on CFER provide a conservative measure of market inefficiency due to market frictions; smaller non-optionable stocks are subject to larger market frictions, and transaction costs, which we show to be the dominant type of frictions for optionable stocks, were more intense before 1996 (see e.g., Hasbrouck (2009)).

A Proofs for Section 2 and Section 5

A.1 Proof of Theorem 2.1

First, note that dividing equation (7) yields

$$1 = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}] + \frac{1}{S_t} \sum_{l=1}^{L} \frac{\lambda_t^l}{u'(c_t)} \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^S}. \tag{A.1}$$

The following equation follows from the covariance formula $Cov_t(X,Y) = \mathbb{E}_t[XY] - \mathbb{E}_t[X]\mathbb{E}_t[Y]$,

$$\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}] = Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1}) + \frac{\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}]}{R_{t,t+1}^0} \tag{A.2}$$

because $\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*] = 1/R_{t,t+1}^0$. Substituting (A.2) to (A.1) and rearranging terms yields equation (10), where $CFER_{t,t+1}$ is defined as equation (11). □

A.2 Proof of Proposition 2.1

Under the assumption that the proportional transaction cost ρ is the only market frictions, He and Modest (1995) derive the following inequalities:

$$\frac{1-\rho}{1+\rho} \leq \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}] \leq \frac{1+\rho}{1-\rho}. \tag{A.3}$$

Equations (A.1) and (11) show that the expectation term in the middle of the inequalities posed by (A.3) relates to CFER as follows:

$$\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}] = \frac{1}{R_{t,t+1}^0} CFER_{t,t+1} + 1. \tag{A.4}$$

Substituting equation (A.4) to (A.3) and rearranging terms yields equation (21). □

A.3 Proof of Proposition 5.1

Deviations from put-call parity $\widetilde{S}_t(K) - S_t$ can be rewritten as the difference between the observed call price $C_t(K)$ and the hypothetical call price $\widetilde{C}_t(K)$, which is calculated as if put-call parity would hold, that is,

$$\widetilde{C}_t(K) = P_t(K) + S_t - \frac{K + D_{t+1}}{R^0_{t,t+1}}. \quad \text{(A.5)}$$

Let $BS_{call}(IV)$ ($BS_{put}(IV)$) be the Black-Scholes call (put) option function viewed as a function of the implied volatility parameter. Then, by the definition of the BS-IV, $IV^c_t(K)$ and $IV^p_t(K)$ satisfy $C_t(K) = BS_{call}(IV^c_t(K))$ and $P_t(K) = BS_{put}(IV^p_t(K))$, respectively. Moreover, it follows that

$$\widetilde{C}_t(K) = BS_{put}(IV^p_t(K)) + S_t - \frac{K + D_{t+1}}{R^0_{t,t+1}} = BS_{call}(IV^p_t(K)), \quad \text{(A.6)}$$

because the pair of the Black-Scholes European call and put option prices with the same volatility satisfies the put-call parity. This shows that $C_t(K) - \widetilde{C}_t(K) = BS_{call}(IV^c_t(K)) - BS_{call}(IV^p_t(K))$. Therefore, a first-order Taylor series approximation of $BS_{call}(IV^c(K)) - BS_{call}(IV^c(K))$ around the mid volatility point $(IV^c_t(K) + IV^p_t(K))/2$ yields

$$C_t(K) - \widetilde{C}_t(K) = BS_{call}(IV^c_t(K)) - BS_{call}(IV^p_t(K)) \approx \mathcal{V}_t(K)(IV^c_t(K) - IV^p_t(K)), \quad \text{(A.7)}$$

where $\mathcal{V}_t(K)$ is the Black-Scholes *vega*, $\partial BS_{call}(\sigma)/\partial\sigma$, evaluated at $(IV^c_t(K)+IV^p_t(K))/2$. By substituting this approximation in equation (13), we obtain equation (24). This derivation shows that the approximation error in (24) stems from the higher-order terms of the Taylor series approximation of $BS_{call}(IV^c_t(K)) - BS_{call}(IV^p_t(K))$. □

A.4 Proof of Proposition 5.2

Substituting the definition of S^U_t and S^L_t in equation (25) yields

$$DOTS_t = \frac{1}{S_t}\left(C^{mid}_t(K) - P^{mid}_t(K) - S_t + \frac{1}{2}\left(1 + \frac{1}{R^0_{t,t+1}}\right)K + \frac{D_{t+1}}{2R^0_{t,t+1}}\right), \quad \text{(A.8)}$$

where C_t^{mid} and P_t^{mid} are the mid price of American options. By the definition of η_t^c and η_t^p, $C_t := C_t^{mid} - \eta_t^c$ and $P_t := P_t^{mid} - \eta_t^p$ are the European option prices. Then, by substituting the definition of the synthetic stock price (equation (12)), we obtain

$$DOTS_t = \frac{\widetilde{S}_t(K) - S_t}{S_t} + \frac{1}{S_t}\left[\left(\eta_t^c - \frac{D_{t+1}}{2R_{t,t+1}^0}\right) - \left(\eta_t^p - \frac{1}{2}\left(1 - \frac{1}{R_{t,t+1}^0}\right)\right)\right]. \tag{A.9}$$

Since the first term in the right hand side of equation (A.9) is $CFER_{t,t+1}^{MF}(K)/R_{t,t+1}^0$, we prove equation (26). □

B Description of variables

Relative bid-ask spread (BAS): We calculate the daily relative bid-ask spread as $BAS_d^i = (S_d^{ask,i} - S_d^{bid,i})/(0.5(S^{ask,i} + S^{bid,i}))$. Then, we average the daily bid-ask spread over the past one year. We require there are at least 200 non-missing observations. Data are obtained from the CRSP database.

Amihud's illiquidity measure: We calculate daily Amihud's (2002) illiquidity measure as the ratio of the absolute daily return to the dollar trading volume, $Illiq_d^i = |R_d^i|/(S_d^i Vol_d^i)$, where R_d^i and Vol_d^i are the daily return and the trading volume of i-th stock on day d. Then, we average daily illiquidity measure over the past one year. We require there are at least 200 non-missing observations. The stock returns, stock prices, and trading volumes are obtained from the CRSP database. The trading volume of the NASDAQ equities is adjusted by following Gao and Ritter (2010).

SIZE: Size is the natural logarithm of the market equity. The market equity is calculated as the product of the number of outstanding share with the price of the stock at the end of each month. Data are obtained from the CRSP database.

Idiosyncratic volatility (IVOL): In each month, we regress the daily excess returns over the past 12 months on the Fama and French (1993) three factors to obtain the residual time-series ε_d^i. Then, we calculate the idiosyncratic volatility (IVOL) as

$$IVOL_t^i = \sqrt{\frac{1}{N(d)-1}\sum_{d \in D}(\varepsilon_d^i)^2},$$

where D is the set of non-missing days in the past 12 months. We require there are at least 200 non-missing observations. Stock return data are obtained from the CRSP database and the Fama and French (1993) three factors data are obtained from Kenneth French's website.

Beta: In each month, we regress daily stock excess returns over past 12 months on the daily excess market return to obtain the beta. We require there are at least 200 non-missing observations. Stock return data are obtained from the CRSP database. We use the excess market return provided at Kenneth French's website.

Relative short interest (RSI): The relative short interest (RSI) is calculated as the ratio of the number of short interest to the number of outstanding share. The short interest data is obtained from the Compustat North America, Supplemental Short Interest File via the WRDS. Until the end of 2006, the Compustat records the short interest at the middle of any given month (typically 15th day of each month). Since 2007, the short interest file contains the short interest at the middle of months and the end of months. We use the end-of-month short interest data since 2007 because we sort stocks in portfolios at the end-of-each month in our analysis. The number of outstanding share is obtained from the CRSP database.

Estimated shorting fee (ESF): We follow Boehme et al. (2006) to calculate the estimated shorting fee as

$$\begin{aligned} ESF = {} & 0.07834 + 0.05438VRSI - 0.00664VRSI^2 + 0.000382VRSI^3 - 0.5908Option \\ & + 0.2587Option \cdot VRSI - 0.02713Option \cdot VRSI^2 + 0.0007583Option \cdot VRSI^3, \end{aligned}$$

where $VRSI$ is the *vicile* ranking of the RSI, that is, $VRSI$ takes the value 1 if the firm's RSI is below 5th percentile, 2 if the RSI is between 5th and 10th percentile and so on. *Option* is a dummy variable that takes 1 if option trading volume in the month is non-zero and takes 0 otherwise. Option trading volume data is obtained from the OM database.

Book-to-Market equity (B/M): We follow Davis et al. (2000) to measure book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. From June of each year t to May of $t+1$, the book-to-market equity (B/M) is calculated as the ratio of the book equity for the fiscal year ending in calendar year $t-1$ to the market equity at the end of December of year $t-1$. We treat non-positive B/M data as missing.

Profitability: We follow Fama and French (2015) to measure profitability as revenues (Compustat annual item REVT) minus cost of goods sold (item COGS) if available, minus selling, general, and administrative expenses (item XSGA) if available, minus interest expense (item XINT) if available all divided by (non-lagged) book equity. From June of year t to May of $t+1$, we assign profitability for the fiscal year ending in calendar year $t-1$.

Investment: We follow Fama and French (2015) to measure investment as the change in total assets (Compustat annual item AT) from the fiscal year ending in year $t-1$ to the fiscal year ending in t, divided by $t-1$ total assets. From June of year t to May of $t+1$, we assign investment for the fiscal year ending in calendar year $t-1$.

Turnover rate: We calculate daily turnover rate as the ratio of trading volume to the number of outstanding share. Then, we average daily turnover rate over the past one year. We require there are at least 200 non-missing observations. Trading volume and the number of outstanding share are obtained from the CRSP database. The trading volume of the NASDAQ equities is adjusted by following Gao and Ritter (2010).

Implied-volatility spread (IVS): We follow Bali and Hovakimian (2009) to construct IVS. Specifically, we keep IV data for options which have (i) positive bid price, (ii) positive open interest, (iii) bid-ask spread is smaller than 50% of the mid price. Then, we average all available IVS extracted from options with maturities between 30 days and 91 days and with the absolute value of the log moneyness $|\log(K/S)|$ smaller than 0.1.

DOTS: We follow Goncalves-Pinto et al. (2017) to keep pairs of call and put options with the same maturity and strike if (i) their day-to-maturity is between 8-days and 31-days, (ii) their IV does not exceed 250%, (iii) their bid prices are strictly positive and (iv) their open interest is greater than zero.

On each end of month t, DOTS of i-th stock at j-th strike price is calculated as follows:

$$DOTS_{t,j}^i = \frac{\frac{S_j^{i,U}+S_j^{i,L}}{2} - S_t^i}{S_t^i},$$

where $S_j^{i,U} = C_t^{i,ask}(K_j) - P_t^{i,bid}(K_j) + K_j + PVD_t^i$ and $S_j^{i,L} = C_t^{i,bid}(K_j) - P_t^{i,ask}(K_j) + PVK_{t,j}^i$. PVD_t^i and $PVK_{t,j}^i$ are the present value of dividend payments and the strike price K_j. Then, DOTS of i-th stock in month t is calculated as

$$DOTS_t^i = 100 \times \sum_{j=1}^{J} \frac{(C_t^{i,ask}(K_j) - C_t^{i,bid}(K_j) + P_t^{i,ask}(K_j) - P_t^{i,bid}(K_j))^{-1}}{\sum_{k=1}^{J}(C_t^{i,ask}(K_k) - C_t^{i,bid}(K_k) + P_t^{i,ask}(K_k) - P_t^{i,bid}(K_k))^{-1}} DOTS_{t,j}^i,$$

where J is the number of option pairs. Option and dividend data are obtained from the OM database.

C CFER estimation: Size of biases

Theorem 2.2 shows that CFER equals the sum of two terms: the model-free $CFER^{MF}_{t,t+1}(K)$ term and the unobservable $U_{t,t+1}(K)$ term, which is a function of the effect of frictions on market option prices. In this Section, we quantify the magnitude of the bias in our baseline model-free estimator AVE-CM CFER, which we denote by $\overline{U}_{t,t+1}$. The bias term $\overline{U}_{t,t+1}$ is a weighted average of the bias term $U_{t,t+1}(K)$ for each pair of call and put options involved in the calculation of AVE-CM CFER (see equation (13)). To assess the magnitude of $U_{t,t+1}(K)$, which is proportional to $M^c_t(K) - M^p_t(K)$ (equation (15)), we examine three alternative ways of modeling the effect of market frictions on individual option prices, $M^c_t(K)$ and $M^p_t(K)$. Then, we assess the magnitude of $\overline{U}_{t,t+1}$, which is the average of $U_{t,t+1}(K)$ across strikes and maturities.

Two remarks are in order at this point. First, to quantify the size of the omitted $U_{t,t+1}(K)$ term, one needs to introduce additional assumptions on the effect of frictions on option prices/returns. However, our theoretical result (Theorem 2.2) holds regardless of the additional assumptions on $M^c_t(K)$ and $M^p_t(K)$. Second, the subsequent analysis reveals that $\overline{U}_{t,t+1}$ is negligible compared to the model-free AVE-CM CFER. However, this does not imply that the effect of market frictions on option prices and returns is negligible. Indeed, Frazzini and Pedersen (2012) and Hitzemann et al. (2017) document that this is not the case. In Appendix C.4, we discuss this point further.

C.1 $M^c_t(K)$ and $M^p_t(K)$ modeled as measurement errors

Assume that $M^c_t(K)$ and $M^p_t(K)$ follow a zero-mean *i.i.d.* random variable. This setup is in line with Bliss and Panigirtzoglou (2002) and Dennis and Mayhew (2009), who assume that observed option prices contain zero-mean measurement errors arising from various frictions such as illiquidity issues and discrete option price quotes.

In this setup, AVE-CM CFER is unbiased because the unconditional mean of $U_{t,t+1}(K)$ equals zero. To evaluate the order of the magnitude of the bias in AVE-CM CFER, we follow Bliss and Panigirtzoglou (2002) and Dennis and Mayhew (2009) to assume that $M_t^c(K)$ and $M_t^p(K)$ follow an $i.i.d.$ uniform distribution over $[-d/2, d/2]$, where $d > 0$ is the width of the support of the uniform noise variable. When N pairs of call and put options are involved in the calculation of AVE-CM CFER, the bias term in the estimated CFER is the average of $2N$ $i.i.d.$ uniform random variables scaled by $R^0_{t,t+1}/S_t$.

In our dataset, the one-month risk-free rate is on average $R^0_{t,t+1} = 1.002$ (i.e., 20 bps per month), the median stock price is around $S_t = \$30$. The median number of pairs of call and put options used to estimate AVE-CM CFER is $N = 3$. Regarding the value of d, we follow Dennis and Mayhew (2009) and set d equal to the tick size of option quotes, which is at most \$0.1 according to the CBOE contract specification. The previous literature uses this value to consider the rounding error in option quotes; if the true option price is rounded to the nearest discrete quote, the maximal size of the measurement error is $d/2$. Given these values, we can numerically calculate the probability distribution of $\overline{U}_{t,t+1}$ and we find that $|\overline{U}_{t,t+1}|$ is less than 6.5 bps with probability greater than 90%.[24] Since the AVE-CM CFER ranges from -1.24% to +0.89% per month in a 5th to 95th percentile range (see Table 1), the unobserved term $\overline{U}_{t,t+1}$ is negligible.

Next, to provide more conservative evaluation, we examine an alternative larger value of $d = \$0.25$, which is the average dollar bid-ask spread of the options we use to estimate AVE-CM CFER, calculated based on OM database. This setup considers the possibility of the mid-option prices (or IVs calculated from the mid prices) containing measurement errors due to the existence of option bid-ask spreads. In this case, $|\overline{U}_{t,t+1}|$ is smaller than 16 bps with the probability approximately equal to 90%. Again, this magnitude is much smaller than the variations in the estimated AVE-CM CFER. These results imply that measurement errors due to discrete quotes and wide bid-ask spread have a limited effect on the determination of CFER.

[24] For simplicity, we assume that the equally-weighted average is taken across strikes and two maturities.

C.2 $M_t^c(K)$ and $M_t^p(K)$ modeled as the embedded leverage effect

Frazzini and Pedersen (2014) theoretically and empirically show that investors prefer assets which have high beta, when their leverage constraints are binding. Based on this so-called betting against beta theory, Frazzini and Pedersen (2012) document that the returns of options are lower because options provide embedded leverage and attract demand from leverage-constrained investors. In particular, they document that option returns are lower by 1.25% per month per unit of embedded leverage.

In line with their empirical findings, we model the CFER term arising due to the embedded leverage effect as $k\Omega_t(K)$, where $\Omega_t(K)$ is option's embedded leverage and k is the sensitivity of option returns to the embedded leverage. Call (put) option's embedded leverage is defined as $\Omega_t^c(K) = |\Delta_t^c(K)S_t/C_t(K)|$ ($\Omega_t^p(K) = |\Delta_t^p(K)S_t/P_t(K)|$), where $\Delta_t^c(K)$ ($\Delta_t^p(K)$) is the call (put) option's delta. Then, option returns are expressed as

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}^c(K)] - R_{t,t+1}^0 = -R_{t,t+1}^0 Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1}^c(K)) + k\Omega_t^c(K), \tag{C.1}$$

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}^p(K)] - R_{t,t+1}^0 = -R_{t,t+1}^0 Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1}^p(K)) + k\Omega_t^p(K), \tag{C.2}$$

where $R_t^c(K) = (S_{t+1} - K)^+/C_t$ and $R_t^p(K) = (K - S_{t+1})^+/P_t$ are the return of call and put options, respectively. Given that it can be shown that equations (C.1) and (C.2) are equivalent to $M_t^c(K) = kC_t\Omega_t^c(K)/R_{t,t+1}^0$ and $M_t^p(K) = kP_t\Omega_t^p(K)/R_{t,t+1}^0$, $U_{t,t+1}(K)$ satisfies the following equation under this embedded leverage model (the superscript *el* stands for "embedded leverage"):

$$U_{t,t+1}(K) = U_{t,t+1}^{EL}(K) = -\frac{R_{t,t+1}^0}{S_t}\left(\frac{kC_t\Omega_t^c(K)}{R_{t,t+1}^0} - \frac{kP_t\Omega_t^p(K)}{R_{t,t+1}^0}\right) = k(|\Delta_p(K)| - \Delta_c(K)). \tag{C.3}$$

Equation (C.3) shows that $U_{t,t+1}^{EL}(K)$ can take both negative and positive value since the difference between the absolute value of put and call deltas is positive (negative) for higher (lower) strikes. Moreover, $U_{t,t+1}^{EL}(K)$ is close to zero around the at-the-money point (i.e., strikes where options' deltas are close to 0.5). This suggests that the distribution of $U_{t,t+1}^{EL}(K)$ for near ATM options is fairly symmetric around zero.

This model allows us to construct the "fully-estimated" CFER for each strike and maturity, defined as $CFER^{EL}_{t,t+1}(K) = CFER^{MF}_{t,t+1}(K) + U^{EL}_{t,t+1}(K)$. Then, we can construct the fully-estimated AVE-CM EL-CFER by following the same procedure described in Section 3.2. To estimate $U^{EL}_{t,t+1}(K)$, we set the coefficient on the embedded leverage k to -1.25% per month by following Frazzini and Pedersen (2012). For option deltas, we use the deltas provided by the OM database.

Next, we assess the magnitude of the $\overline{U}_t$ bias in two ways. First, we investigate the correlation between our baseline model-free AVE-CM CFER (henceforth, AVE-CM MF-CFER, where MF stands for "model-free") and the fully-estimated AVE-CM EL-CFER. The correlation coefficient is 0.96 and hence the two CFER are almost perfectly correlated. Second, we compare the cross-sectional stock return predictive ability of AVE-CM MF-CFER and AVE-CM EL-CFER. If there is no significant difference in their return predictive ability in terms of the alphas of the spread portfolio, this would imply that the embedded leverage effect has only a negligible effect on the estimation of CFER based on deviations from put-call parity. Table A.1, Panel A, shows the average return and $\alpha_{CAPM}, \alpha_{FF3}, \alpha_{FFC}, \alpha_{FF5}, \alpha_{SY}$ of the value-weighted decile spread portfolio where we sort stocks based on the AVE-CM EL-CFER. We can see that the AVE-CM EL-CFER also predicts future stock returns cross-sectionally just as it was the case for the baseline AVE-CM MF-CFER, which ignores the $U^{EL}_{t,t+1}$ term; the average return and alphas are sizable and statistically significant for the AVE-CM EL-CFER. We also calculate the t-statistics of the difference between the portfolio sort results based on AVE-CM MF-CFER and AVE-CM EL-CFER; these are reported in the square brackets. To this end, we examine the average return and alphas of the spread portfolio, where we long the spread portfolio based on MF-CFER and short the spread portfolio based on EL-CFER (that is, we examine a spread portfolio of spread portfolios). We can see that these t-statistics are insignificant. This means that the average returns and alphas of the spread portfolio based on AVE-CM EL-CFER are not statistically significantly different from those based on the baseline AVE-CM MF-CFER. These results suggest that distortions in option prices due to the embedded leverage effect have a negligible effect on the estimation of stocks' CFER.

[Table A.1 about here.]

C.3 $M_t^c(K)$ and $M_t^p(K)$ modeled as margin constraints

Finally, we assume that margin constraints are the only type of market frictions. We consider this particular type of market frictions because the literature documents that margin constraints affect option returns (e.g., Santa-Clara and Saretto (2009), Hitzemann et al. (2017)) and hence it is possible that margin constraints can result in non-negligible $U_{t,t+1}(K)$.

Under this setup, $U_{t,t+1}(K)$ is given by the following equation (the superscript MC stands for "margin constraints"):

$$U_{t,t+1}(K) = U_{t,t+1}^{MC}(K) = \frac{R_{t,t+1}^0}{S_t}\frac{\lambda_t^{MC}}{u'(c_t)}\left(\frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)}\right). \tag{C.4}$$

To estimate $U_{t,t+1}^{MC}(K)$, we need to specify the margin constraint function g_t^{MC} and we also need empirical evidence on the magnitude of the Lagrange multiplier $\lambda_t^{MC}/u'(c_t)$. First, we follow Gârleanu and Pedersen (2011) to formalize the margin constraint function g_t^{MC} as follows:

$$g_t^{MC}(\boldsymbol{\theta}_t) := W_t - |\theta_t^S|\mu_t^S S_t - \sum_{K\in\mathcal{K}_t}\Big(|\theta_t^c(K)|\mu_t^c(K)C_t(K) + |\theta_t^p(K)|\mu_t^p(K)P_t(K)\Big) \geq 0, \tag{C.5}$$

where $\mu_t^S > 0$, $\mu_t^c(K) > 0$ and $\mu_t^p(K) > 0$ are the *margin rates*, that is, $\mu_t^S S_t$, $\mu_t^c(K)C_t(K)$ and $\mu_t^P(K)P_t(K)$ are the initial margin traders need to hold when they trade one unit of the corresponding asset. This constraint imposes that the aggregated margins the agent need to hold should not exceed her wealth W_t. The absolute values of asset allocations are involved since typically traders need to hold margins both when they long and short assets (see also the discussion in Gârleanu and Pedersen (2011)). The margin rates of options, $\mu_t^c(K)$ and $\mu_t^p(K)$ are determined by the option exchange rule and depend on the strike price and whether options are bought or sold. Under the CBOE margin rule, they are given by the following equations (see Hitzemann et al. (2017) for a detailed discussion):[25]

$$\mu_t^i(K) = 1, \quad \text{when an option is longed, } \theta_t^i(K) > 0,\ i \in \{c, p\} \tag{C.6}$$

$$\mu_t^c(K) = \frac{\max(0.2S_t - (K - S_t)^+, 0.1S_t)}{C_t(K)}, \quad \text{when a call option is shorted, } \theta_t^c(K) < 0 \tag{C.7}$$

$$\mu_t^p(K) = \frac{\max(0.2S_t - (S_t - K)^+, 0.1K)}{P_t(K)}, \quad \text{when a put option is shorted, } \theta_t^p(K) < 0 \tag{C.8}$$

To simplify the calculation of the call and put margin rates, we focus on strikes which satisfy $8/9 \leq K/S_t \leq 1.1$. This examined range of strikes is not restrictive because we only use options whose moneyness satisfy $0.9 \leq K/S_t \leq 1.1$ in our empirical exercises. In this case, the calculation of the two max functions in equations (C.7) and (C.8) yields $\mu_t^c(K)C_t(K) = 0.2S_t - (K - S_t)^+$ and $\mu_t^p(K)P_t(K) = 0.2S_t - (S_t - K)^+$. Under these specifications of g_t^{MC}, $\mu_t^c(K)$ and $\mu_t^p(K)$, we obtain the following expression for U_t^{MC}:

Proposition C.1. *For any strike price K satisfying $8/9 \leq K/S_t \leq 1.1$, the following equation holds:*

$$U_{t,t+1}^{MC}(K) = E_t(K) \times R_{t,t+1}^0 \lambda_t^{MC} / u'(c_t), \quad \textit{where} \tag{C.9}$$

$$E_t(K) = \begin{cases} (C_t(K) - P_t(K))/S_t & \textit{when } \theta_t^c(K) > 0 \textit{ and } \theta_t^p(K) > 0 \\ -(S_t - K)/S_t & \textit{when } \theta_t^c(K) < 0 \textit{ and } \theta_t^p(K) < 0 \\ (0.2 + [C_t(K) - (S_t - K)^+]/S_t) & \textit{when } \theta_t^c(K) > 0 \textit{ and } \theta_t^p(K) < 0 \\ -(0.2 + [P_t(K) - (K - S_t)^+]/S_t) & \textit{when } \theta_t^c(K) < 0 \textit{ and } \theta_t^p(K) > 0. \end{cases} \tag{C.10}$$

Proof. See Appendix C.5. □

[25] Even though each option exchange can have a different margin rule, Hitzemann et al. (2017) document that the CBOE margin rule is the de facto standard margin rule in the U.S. option exchanges.

Equation (C.10) shows that the sign and magnitude of $E_t(K)$ (and hence those of $U^{MC}_{t,t+1}(K)$) depends on the signs of thetas and the moneyness of options in a complex manner. For example, $E_t(K)$ is always positive (negative) for the third (fourth) case. On the other hand, for higher moneyness options (i.e., $K > S_t$), $E_t(K)$ is negative for the first case while it is positive for the second case. These signs flip for lower moneyness options. Our empirical analysis of $E_t(K)$ suggests that the distribution of $E_t(K)$ (and hence $U_t(K)$) is close to symmetric around zero.

We estimate $U^{MC}_{t,t+1}(K) = E_t(K)R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ by relying on previous empirical evidence. To this end, we separately estimate $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ and $E_t(K)$ and take their product. First, $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ corresponds to the shadow cost of capital in Gârleanu and Pedersen (2011), which is shown to be equal to the spread between the uncollateralized and collateralized risk-free bond rates. We can show that the spread of these two bond rates coincides with $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ if we extend our model to include both the collateralized and uncollateralized risk-free bonds.[26] Gârleanu and Pedersen (2011) find that the shadow cost of capital is time-varying and become higher during market distress periods. Moreover, their empirical estimations and calibration results suggest that the shadow cost during the recent financial crisis is about 10% per year (page 1982 and Figure 1).

We examine three specifications for $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$. In the first specification, it is assumed to be constant and equal to 10% per year, based on the maximum of the estimated shadow cost of capital in Gârleanu and Pedersen (2011). In the second specification, we set $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ as 5% per year (constant) considering the fact that 10% is the

[26] Let $R^u_{t,t+1}$ be the return of the uncollateralized bond and θ^u_t be the market-maker's position on the uncollateralized bond. The equations for the consumption (4) and the margin constraint (C.5) change to

$$c_t = W_t - \theta^0_t - \theta^u_t - \theta^S_t S_t - \sum_{K\in\mathcal{K}_t}\left[\theta^c_t(K)C_t(K) + \theta^p_t(K)P_t(K)\right],$$

$$g^{MC}_t(\boldsymbol{\theta}_t) = W_t - \theta^u_t - |\theta^S_t|\mu^S_t S_t - \sum_{K\in\mathcal{K}_t}\left[|\theta^c_t(K)|\mu^c_t(K)C_t(K) + |\theta^p_t(K)|\mu^p_t(K)P_t(K)\right] \geq 0.$$

The first order conditions of the collateralized bond (θ^0_t) is unchanged and given by $1 = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R^0_{t,t+1}]$, whereas the first order condition of the uncollateralized bond (θ^u_t) is $1 = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R^u_{t,t+1}] - \lambda^{MC}_t/u'(c_t)$. From these two first order conditions, we obtain $R^u_{t,t+1} - R^0_{t,t+1} = R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$.

highest value during the financial crisis and thus the time-series average of the shadow price of capital is much lower. To consider the time-varying nature of the shadow cost of capital, we also examine the case where $R^0_{t,t+1}\lambda_t^{MC}/u'(c_t)$ is given by the scaled TED spread, whose maximum value matches 10% per year during the financial crisis.[27]

For each one of the four cases in equation (C.10), the value of $E_t(K)$ can be calculated as long as the sign of the call and put positions are known. To this end, we impose additional structure of the market participants, following Gârleanu et al. (2009) and Hitzemann et al. (2017). In particular, we assume there are two types of agents, the market-maker and the end-user. We identify the *agent*, who is the market participant we focused on in the main body, as the market-maker.[28]

Let $d_t^c(K)$ and $d_t^p(K)$ be the end-users' demand for the call and put option, respectively. Then, at equilibrium, $d_t^c(K) = -\theta_t^c(K)$ and $d_t^p(K) = -\theta_t^p(K)$ hold because options are in zero net supply. Therefore, it follows that $sgn(\theta_t^c) = -sgn(d_t^c)$ ($sgn(\theta_t^p) = -sgn(d_t^p)$). We estimate the signs of the end-users' demand instead of the market-maker's position and take the opposite signs.

To infer the signs of the end-users' demand, we rely on Gârleanu et al.'s (2009) empirical finding that end-user's demand for option is highly related to the options' *expensiveness*, which they proxy by the difference between the historical volatility and the implied volatility. Specifically, we assume that the options' expensiveness is above (below) the reference point s if and only if the end-user's demand $d_t(K)$ is positive (negative), that is, the end-user buys (sells) the option:

$$expensiveness_t^i(K) < s \;\Leftrightarrow\; d_t^i(K) < 0 \;\Leftrightarrow\; \theta_t^i(K) > 0, \quad i \in \{c, p\}. \tag{C.11}$$

We estimate the expensiveness measure (i.e., the left hand side of equation (C.11)) as

[27] Note that Gârleanu and Pedersen (2011) regress the estimated shadow price of capital on the TED spread to obtain the coefficient on the TED spread about 1.8, while we multiply the TED spread by the factor of about 3.3 to match the 10% maximum value. Our choice of the scaling factor is conservative for our robustness check purposes, because it results in bigger (absolute value of) estimated $U^{MC}_{t,t+1}$.

[28] This is in line with the definition of the *agent* in the main body since the option market-maker (i) is a sophisticated marginal investor (as assumed in Gârleanu et al. (2009) and Hitzemann et al. (2017)) and (ii) takes part in both the stock and option market.

the difference between the BS-IVs and the one-year historical volatility, both of which are provided by the OM database. To select the value of s, we rely on Gârleanu and Pedersen's (2011) finding that the end-user is the net seller of individual options, that is, the end-user sells more options than buys, implying that there are more "cheap" options than "expensive" options. This suggests that the proportion of options whose expensiveness is below s should be above 50%. Given this finding, we examine three values for the reference point, $s = 0$, $s = 0.01$ and $s = 0.02$. Under these parameters, the estimation rule (C.11) yields the results that in our sample, roughly 50%, 55%, and 62% of options are "cheap," respectively.

In analogy to Appendix C.2, we construct the "fully-estimated" CFER under the margin constraints model, $CFER^{MC}_{t,t+1}(K)$ as $CFER^{MC}_{t,t+1}(K) = CFER^{MF}_{t,t+1}(K) + U^{MC}_{t,t+1}(K)$ for each strike and maturity, where we estimate the latter term as the product of $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ and $E_t(K)$. Since we examine three cases each for $R^0_{t,t+1}\lambda^{MC}_t/u'(c_t)$ and $E_t(K)$ (by considering three reference point value s to determine the signs of $\theta^c_t(K)$ and $\theta^p_t(K)$), respectively, we have in total nine estimates of $U^{MC}_{t,t+1}(K)$ and hence $CFER^{MC}_{t,t+1}(K)$. Then, we construct the fully-estimated margin-constraints-based AVE-CM CFER (AVE-CM MC-CFER) by following the same procedure described in Section 3.2.

In analogy with the analysis for the embedded leverage model in Appendix C.2, we examine how the incorporation of the margin constraints model-based U term affects the estimated CFER. First, the pairwise correlations between our baseline AVE-CM MF-CFER (which ignores the U term) and each one of the nine AVE-CM MC-CFER are at least 0.998, that is, the baseline estimated CFER and all of the nine $U^{MC}_{t,t+1}$-adjusted CFER are almost perfectly correlated. Next, we compare the predictive ability of AVE-CM MF-CFER and that of the nine AVE-CM MC-CFER in terms of the alphas of the spread portfolios. Table A.1, Panel B, reports the results. First, similar to AVE-CM EL-CFER, all nine margin constraints-based CFER strongly predict the cross-section of future stock returns; the average return and alphas are sizable and statistically significant for each one of the nine alternative methods to compute $U^{MC}_{t,t+1}$. We also calculate the

t-statistics of the differences between the baseline result and each one of the AVE-CM MC-CFER results and they are reported in the square brackets. We can see that all nine results based on AVE-CM MC-CFER are not statistically significantly different from the baseline result. These results suggest that distortions in option prices due to margin constraints have a negligible effect on the estimation of stocks' CFER.

C.4 Why is the U term negligible even though market frictions affect option returns?

Even though Frazzini and Pedersen (2012) and Hitzemann et al. (2017) document that the embedded leverage effect and the margin constraints have a non-negligible effect on option returns, respectively, our analysis suggests that these two types of market frictions have a negligible effect on $\overline{U}_{t,t+1}$. This is possible due to the following two reasons.

First, the findings in the previous literature on option returns suggest that the ratios $M_t^c(K)/C_t(K)$ and $M_t^p(K)/P_t(K)$ are not negligible. To see this point for the case of call options (put options can be treated similarly), the transformation of the first-order condition of the call option, equation (8), yields

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}^c(K)] - R_{t,t+1}^0 = -R_{t,t+1}^0 Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1}^c(K)) - R_{t,t+1}^0 \frac{M_t^c(K)}{C_t(K)}, \qquad \text{(C.12)}$$

where the second term in the right-hand side denotes the effect of market frictions on call option returns. On the other hand, $U_t(K)$ becomes small if $M_t^c(K)/S_t$ and $M_t^p(K)/S_t$ are small (equation (15)). Empirically, these ratios are much smaller than the ratios $M_t^c(K)/C_t(K)$ and $M_t^p(K)/P_t(K)$ because the denominators of the former (i.e., the stock price) is much larger than those of the latter (i.e., option prices).[29] Therefore, it is possible that the effect of market frictions on option returns is not negligible, yet $U_t(K)$ is negligible.

Second, $U_{t,t+1}(K)$ is proportional to the difference between $M_t^c(K)$ and $M_t^p(K)$. The-

[29]For example, $C_t(K)/S_t$ is less than 0.05 for a one-month ATM option price under the BS model with typical volatility of 40%.

refore, they would mostly offset each other in the case where they have the same sign and they are of similar size. Their signs are always the same for the embedded leverage effect model because $M_t^c(K) = k\Delta_t^c(K)$ and $M_t^p(K) = k|\Delta_t^p(K)|$ always have the same sign (see equation (C.3)). For the margin constraints model, $M_t^c(K)$ and $M_t^p(K)$ have the same sign when the agent's allocation to call and put options have the same sign. We find that call option and put options' "expensiveness" are strongly correlated, and hence the signs of $\theta_t^c(K)$ and $\theta_t^p(K)$ determined based on equation (C.11) are the same for approximately 90% of call and put option pairs used to estimate AVE-CM CFER, regardless of the three choices of the threshold value s. Moreover, the degree of the offsetting effect is stronger for near ATM options because the absolute value of the delta of call and put options are similar, and the amount of margins required for call and put options are similar when the sign of allocations to them (θ_t^c and θ_t^p) are the same. These results suggest that the offsetting effect between $M_t^c(K)$ and $M_t^p(K)$ reduces the size of $U_t(K)$ for most of the cases, especially for near ATM options which we use in the estimation of CFER.

C.5 Proof of Proposition C.1

It suffices to show $-\frac{1}{S_t}\left(\frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}\right) = E_t(K)$. The calculation of the partial derivatives given the margin constraint function, equation (C.5), yields

$$-\frac{1}{S_t}\left(\frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^{MC}(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}\right) = \frac{1}{S_t}\left[sgn(\theta_t^c(K))\mu_t^c(K)C_t(K) - sgn(\theta_t^p(K))\mu_t^p(K)P_t(K)\right], \tag{C.13}$$

where the sign function $sgn(x)$ returns 1 (-1) if x is positive (negative). Then, we can further calculate the right hand side of equation (C.13) for each of four possible combinations of the signs of $\theta_t^c(K)$ and $\theta_t^p(K)$.

When $\theta_t^c(K) > 0$ *and* $\theta_t^p(K) > 0$, the margin rule is $\mu_t^c(K) = \mu_t^p(K) = 1$ and the right hand side of equation (C.13) boils down to $(C_t - P_t)/S_t$. When $\theta_t^c(K) < 0$ *and* $\theta_t^p(K) < 0$, the margin rule are given by $\mu_t^c(K)C_t(K) = 0.2S_t - (K - S_t)^+$ and $\mu_t^p(K)P_t(K) = 0.2S_t - (S_t - K)^+$ under our assumption that $8/9 \leq K/S_t \leq 1.1$, . Therefore, the right hand side of equation (C.13) simplifies to

$$\frac{1}{S_t}\left[-(0.2S_t-(K-S_t)^+)+(0.2S_t-(S_t-K)^+)\right]=-\frac{S_t-K}{S_t}. \tag{C.14}$$

When $\theta_t^c(K)>0$ *and* $\theta_t^p(K)<0$, the margin rule becomes $\mu_t^c(K)=1$ and $\mu_t^p(K)P_t(K)=0.2S_t-(S_t-K)^+$ and the right hand side of equation (C.13) is calculated as

$$\frac{1}{S_t}\left[C_t+(0.2S_t-(S_t-K)^+)\right]=0.2+[C_t-(S_t-K)^+]/S_t. \tag{C.15}$$

Finally, when $\theta_t^c(K)<0$ *and* $\theta_t^p(K)>0$, the margin rule becomes $\mu_t^c(K)C_t(K)=0.2S_t-(K-S_t)^+$ and $\mu_t^p(K)=1$ and the right hand side of equation (C.13) is calculated as

$$-\frac{1}{S_t}\left[P_t+(0.2S_t-(K-S_t)^+)\right]=-\left(0.2+[P_t-(K-S_t)^+]/S_t\right). \tag{C.16}$$

These complete the proof of equation (C.10). □

D The risk-free bond market with market frictions

In the main body, we assume that market frictions have no effect on the risk-free bond to keep the exposition simple. In this Appendix, we provide the extended model where we relax this assumption. Then, we show that this modification has a negligible effect on our model-free CFER measure. This justifies our approach in the main model to employ a simplifying assumption regarding the effect of frictions on the risk-free bond market.

D.1 The generalized definition of CFER

When market frictions also affect the risk-free bond, the first-order condition for the bond analogous to equation (7) is given by

$$1=\mathbb{E}_t^{\mathbb{P}}[m^*_{t,t+1}R^0_{t,t+1}]+M^0_{t,t+1}, \tag{D.1}$$

where $M^0_{t,t+1} = \sum_{l=1}^{L}(\lambda^l_t/u'(c_t))\partial g^l_t(\boldsymbol{\theta}_t)/\partial\theta^0_t$. By defining $\widetilde{R}^0_{t,t+1} = 1/\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}]$, equation (D.1) can be transformed into

$$\widetilde{R}^0_{t,t+1} - R^0_{t,t+1} = \widetilde{R}^0_{t,t+1}M^0_{t,t+1}. \tag{D.2}$$

The difference $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}$ can be interpreted as the effect of frictions on the risk-free rate. Consistent with this interpretation, equation (D.2) shows that $\widetilde{R}^0_{t,t+1} = R^0_{t,t+1}$ holds if and only if the effect of frictions on the risk-free bond is zero (i.e., $M^0_t = 0$).

By using the new expression for $\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}]$ to transform the Euler equation (7), the asset pricing equation is generalized to

$$\mathbb{E}^{\mathbb{P}}_t[R_{t,t+1}] - R^0_{t,t+1} = -\frac{Cov^{\mathbb{P}}_t(m^*_{t,t+1}, R_{t,t+1})}{\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}]} - \widetilde{R}^0_{t,t+1}\frac{M^S_{t,t+1}}{S_t} + (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}). \tag{D.3}$$

Since CFER is the part of the expected return which is not explained by the covariance risk premium, the definition of CFER is generalized to

$$CFER_{t,t+1} = -\widetilde{R}^0_{t,t+1}\frac{M^S_{t,t+1}}{S_t} + (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}). \tag{D.4}$$

Note that equation (D.4) nests the definition of CFER presented in the main body; in the case where the risk-free rate is not affected by frictions, the equality $\widetilde{R}^0_{t,t+1} = R^0_{t,t+1}$ holds and equation (D.4) boils down to equation (11). Moreover, this generalization of the definition of CFER does not affect the cross-sectional variation in CFER because $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}$ is common across all stocks; the variation in CFER is determined again by the value of $M^S_{t,t+1}/S_t$ just as it was the case with the definition of CFER in the main body, equation (11). As a result, the evidence on the cross-sectional predictability of CFER presented in Section 4 is not affected by assuming that there is no effect of market frictions on the risk-free bond market.

D.2 Scaled deviations from put-call parity

Under the generalized framework, the synthetic stock price $\widetilde{S}_t(K) = C_t(K) - P_t(K) + (K + D_{t+1})/R^0_{t,t+1}$ becomes

$$\begin{aligned}\widetilde{S}_t(K) = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1} + D_{t+1})] + (M^c_t(K) - M^p_t(K))\\ + \left(\frac{1}{R^0_{t,t+1}} - \frac{1}{\widetilde{R}^0_{t,t+1}}\right)(K + D_{t+1}).\end{aligned} \tag{D.5}$$

The last term in the right-hand side of equation (D.5) reflects the fact that the effect of frictions on the risk-free bond transmits to the synthetic stock price because the synthetic stock position involves the investment in the risk-free bond by the amount of $K + D_{t+1}$. Then, taking the difference between S_t and $\widetilde{S}_t(K)$ yields

$$S_t - \widetilde{S}_t(K) = M^S_t - (M^c_t(K) - M^p_t(K)) - \left(\frac{1}{R^0_{t,t+1}} - \frac{1}{\widetilde{R}^0_{t,t+1}}\right)(K + D_{t+1}). \tag{D.6}$$

Scaling the both sides of equation (D.6) by $-R^0_{t,t+1}/S_t$ yields

$$CFER^{MF}_{t,t+1} = \frac{R^0_{t,t+1}}{S_t}(\widetilde{S}_t(K) - S_t) = -\frac{R^0_{t,t+1}}{S_t}M^S_t - U_t(K) + \left(\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}\right)\frac{K + D_{t+1}}{\widetilde{R}^0_{t,t+1}S_t}, \tag{D.7}$$

where $U_t(K)$ is the same as equation (15). Subtracting equation (D.7) from (D.4) and rearranging terms yields

$$CFER_{t,t+1} = CFER^{MF}_{t,t+1} + U_t(K) - (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})\left[\frac{K + D_{t+1}}{\widetilde{R}^0_{t,t+1}S_t} - 1 + \frac{M^S_{t,t+1}}{S_t}\right]. \tag{D.8}$$

Equation (D.8) shows that $CFER_{t,t+1}$ now contains an additional unobservable term

$$\underbrace{-(\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})\left[\frac{K + D_{t+1}}{\widetilde{R}^0_{t,t+1}S_t} - 1\right]}_{A_1} \underbrace{-(\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})\frac{M^S_{t,t+1}}{S_t}}_{A_2} \tag{D.9}$$

in addition to the $U_t(K)$ term (see equation (18)).

D.3 The evaluation of the additional term

In what follows, we demonstrate that the additional terms in equation (D.9) due to a non-zero effect of frictions to the risk-free bond market is negligible. Therefore, the model-free CFER (i.e., scaled deviations from put-call parity) still proxies the true CFER accurately even when we allow the risk-free bond market to be affected by frictions just as it was the case with the analysis presented in the main body of the paper, where we allowed for a non-zero effect of frictions to the stock and option market.

We begin by discussing a plausible value for $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}$, which measures the size of the effect of market frictions on the risk-free rate. The effect of market frictions on the risk-free rate has been studied extensively from the perspective of the *risk-free rate puzzle*; the empirically observed risk-free is too low given standard theoretical models with plausible values for the preference parameters. A strand of studies considers a model with market frictions, especially the borrowing constraints, which makes the observed risk-free rate (i.e., $R^0_{t,t+1}$) lower than $\widetilde{R}^0_{t,t+1}$. The consensus in this literature is that $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1} > 0$.

However, there is no consensus on its empirical magnitude. Kogan et al. (2007) consider a borrowing constraints model and report a calibrated simulation result that the short-term risk-free rate is lowered possibly by 1.5% per year. Constantinides et al. (2002) calibrate their borrowing constrained model and report that the borrowing constraints lower the long-term bond rate by about 4% to 6% per year. Even though this value is much higher than that in Kogan et al. (2007), it may be due to the difference in the maturity of bond under consideration. Heaton and Lucas (1996) examine whether borrowing constraints and transaction costs can solve the equity risk premium puzzle and the risk-free rate puzzle simultaneously. They report that unrealistically large transaction costs are necessary to decrease the risk-free rate to solve the risk-free rate puzzle, and in such a case, the model's risk-free rate decreases by about 4% per year.

Given the results in the previous literature, we set $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}$ to 0.5% per month (or 6% per year) in the subsequent discussion. The choice of this value sets a high hurdle to to our attempt to show that the magnitude of the extra term in equation (D.7), which arises due to the effect of frictions on the risk-free bond, is small.

Now, we evaluate A_1 and A_2 in equation (D.9) separately. First, we transform A_1 as

$$A_1 = \frac{\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}}{\widetilde{R}^0_{t,t+1}} \left[\left(\frac{K}{S_t} - 1 + \frac{D_{t+1}}{S_t} \right) - (\widetilde{R}^0_{t,t+1} - 1) \right]. \tag{D.10}$$

Then, taking the absolute value and using $\widetilde{R}^0_{t,t+1} \geq R^0_{t,t+1} \geq 1$ yields

$$|A_1| \leq |\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}| \times \left(\left| \frac{K}{S_t} - 1 \right| + \frac{D_{t+1}}{S_t} + |\widetilde{R}^0_{t,t+1} - 1| \right). \tag{D.11}$$

To further evaluate this inequality, recall that we use only near ATM options ($|K/S_t - 1| \leq 0.1$). Given a plausible yet conservative dividend yield of 4% per year, D_{t+1}/S_t is about 0.01 (= 4%/4) because U.S. firms typically pay dividends quarterly. The value of $\widetilde{R}^0_{t,t+1} - 1 = (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}) + (R^0_{t,t+1} - 1)$ is at most 1% per month (i.e., $\widetilde{R}^0_{t,t+1} \leq 1.01$) under our numerical assumption on $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}$ because the observed risk-free rate $R^0_{t,t+1} - 1$ is at most 0.5% per month during our sample period. Therefore, we obtain

$$|A_1| \leq 0.5\% \times (0.1 + 0.01 + 0.01) \approx 6 \text{ bps}. \tag{D.12}$$

Note that this is an upper bound and usually $|A_1|$ is much smaller because the moneyness of options used is much closer to one (i.e., $|K/S_t - 1| \approx 0$). Therefore, we can conclude that the A_1 term is negligible compared to the variation in the estimated $CFER^{MF}_{t,t+1}$.

Next, we evaluate A_2. To this end, by ignoring the negligible $U_t(K)$ and A_1 terms in equation (D.8), we obtain the following approximation relation:

$$CFER^{MF}_{t,t+1} \approx CFER_{t,t+1} + A_2 = -R^0_{t,t+1} \frac{M^S_{t,t+1}}{S_t} + (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}). \tag{D.13}$$

With some more algebra, we obtain the following approximation relation:

$$A_2 = (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1}) \frac{M^S_{t,t+1}}{S_t} \approx -\frac{(\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})}{R^0_{t,t+1}} CFER^{MF}_{t,t+1} + (\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})^2. \tag{D.14}$$

Under the assumption of $\widetilde{R}^0_{t,t+1} - R^0_{t,t+1} = 0.5\%$, the value of the second term in the right-hand side of equation (D.14) is negligible (0.25 bps). The first term in the right-hand side of equation (D.14) is proportional to $CFER^{MF}_{t,t+1}$ by the factor of $(\widetilde{R}^0_{t,t+1} - R^0_{t,t+1})/R^0_{t,t+1} \approx$ 0.5%. Therefore, this term results in a negligible relative error; when $|CFER^{MF}_{t,t+1}|$ is smaller than 3%, it results in at most only 1.5 bps of absolute error.[30] All in all, we conclude that A_2 is negligible.

To sum up, the additional term in the $CFER^{MF}_{t,t+1}$ formula caused by the effect of frictions on the risk-free rate, equation (D.9), is negligible. Therefore, the model-free CFER (i.e., the scaled deviations from put-call parity) is still a good proxy of the true CFER even when market frictions affect the risk-free bond market.

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[30]The 1st percentile to 99th percentile range of AVE-CM CFER is from -2.9% to +2.1%. Therefore, $|CFER^{MF}_{t,t+1}| \leq 3\%$ holds for almost all samples except a small number of outliers.

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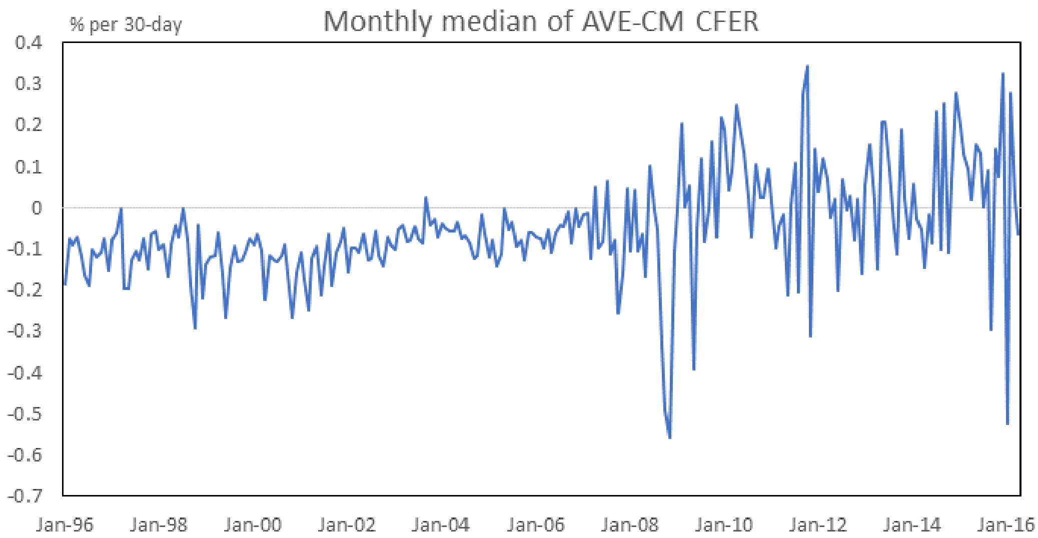
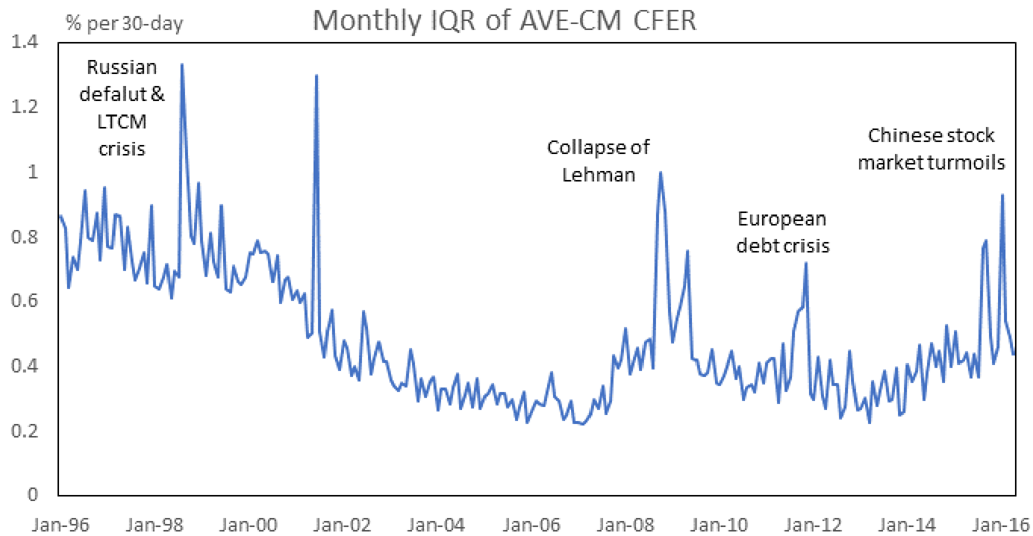


(a) Median



(b) IQR

Figure 1. Time Series of the monthly Median and IQR of AVE-CM CFER. Figure 1a illustrates the time-series of the monthly median of AVE-CM CFER and Figure 1b illustrates the time-series of the monthly IQR (difference between the 75th and 25th percentile points) of AVE-CM CFER. At the end of each month, we calculate the median and IQR of the individual stocks' AVE-CM CFER values. The unit of the y-axis is % per 30-day. The estimation period spans January 1996 to April 2016 (244 months).

Table 1. Estimated CFER: Summary statistics

Entries in Panel A report the summary statistics of the estimated CFER at the end of each month for the four different ways of estimating CFER. These are denoted by a combination of the method of choosing strikes (AVE or ATM) and the method of choosing maturities (CM or CLS) of options. In AVE methods, (1) and (3), we average CFER across available strikes, whereas in ATM methods, (2) and (4), we choose the strike closest to the forward price. In CM methods, (1) and (2), we interpolate CFER across the estimated CFER of traded maturities to obtain a 30-day constant maturity CFER, while in CLS methods, (3) and (4), we choose the traded maturity closest to 30 days. The row for N reports the total number of month-stock CFER observations, the row for IQR reports the interquartile range (75th minus 25th percentile values), and the last row, % of $CFER < 0$, reports the proportion of observations with negatively estimated CFER. The estimation period spans January 1996 to April 2016 (244 months). The unit of statistics (except skewness, kurtosis, and % of $CFER < 0$) is % per 30-day. Entries in Panel B report the pairwise Pearson correlation coefficients between the four estimated CFER measures.

Panel A: Summary statistics of the estimated CFER				
	(1) AVE-CM	(2) ATM-CM	(3) AVE-CLS	(4) ATM-CLS
N	333,234	333,234	347,073	347,073
mean	-0.09	-0.09	-0.10	-0.10
standard deviation	0.88	0.89	1.09	1.10
skewness	-1.95	-1.88	-1.59	-1.53
kurtosis	69.32	68.92	69.97	69.20
minimum	-27.67	-27.67	-35.60	-35.60
5th percentile	-1.24	-1.25	-1.54	-1.55
Median	-0.04	-0.04	-0.04	-0.04
95th percentile	0.89	0.89	1.14	1.15
maximum	24.96	24.96	32.72	32.72
IQR	0.47	0.46	0.60	0.60
% of CFER< 0	55.3%	55.1%	54.9%	54.6%
Panel B: Correlation between different measures of CFER				
	(1) AVE-CM	(2) ATM-CM	(3) AVE-CLS	(4) ATM-CLS
(1) AVE-CM	1			
(2) ATM-CM	0.986	1		
(3) AVE-CLS	0.989	0.974	1	
(4) ATM-CLS	0.973	0.989	0.984	1

Table 2. AVE-CM CFER-sorted decile portfolios: Cross-sectional predictability

Entries in Panel A report the average CFER, average post-ranking return and results for the risk-adjusted returns (α) of the AVE-CM CFER-sorted value-weighted decile portfolios and the spread portfolio, with respect to the CAPM and Carhart (1997) four-factor model. On the last trading day of each month t, stocks are sorted in ascending order based on AVE-CM CFER and then value-weighted decile portfolios are formed. We then calculate the return of these portfolios and the spread portfolio in the succeeding month-($t+1$). Entries in Panel B report the average CFER, average post-ranking return and alphas of the AVE-CM CFER-sorted equally-weighted decile portfolios and the spread portfolio. The estimation period spans January 1996 to April 2016 (244 months) for both Panels. t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in parentheses. The unit of the average returns and alphas (average CFER) is % per month (30-day). N is the average number of stocks in each decile portfolio.

	AVE-CM CFER-sorted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Panel A: Value-weighted portfolios											
Ave. CFER	-1.31	-0.53	-0.31	-0.18	-0.09	-0.01	0.07	0.18	0.36	0.93	2.24
Ave. return	-0.18	0.23	0.54	0.49	0.79	0.89	0.99	0.92	1.15	1.46	1.64
	(-0.36)	(0.60)	(1.58)	(1.64)	(2.57)	(2.82)	(3.20)	(2.73)	(3.19)	(3.38)	(5.77)
α_{CAPM}	-1.15	-0.58	-0.23	-0.25	0.04	0.13	0.24	0.13	0.33	0.55	1.70
	(-5.69)	(-3.41)	(-1.96)	(-2.47)	(0.42)	(1.29)	(2.30)	(1.16)	(2.30)	(2.77)	(5.91)
α_{FFC}	-1.11	-0.62	-0.26	-0.23	0.00	0.12	0.24	0.18	0.44	0.75	1.86
	(-6.52)	(-3.74)	(-2.28)	(-2.28)	(0.02)	(1.16)	(2.38)	(1.50)	(2.54)	(3.52)	(6.56)
N	134.9	135.0	134.9	135.1	134.7	135.3	134.9	135.0	134.9	135.0	—
Panel B: Equally-weighted portfolios											
Ave. CFER	-1.58	-0.55	-0.32	-0.19	-0.09	-0.01	0.07	0.18	0.37	1.14	2.73
Ave. return	-0.35	0.49	0.65	0.76	0.86	0.97	0.93	1.02	1.08	1.38	1.73
	(-0.65)	(1.09)	(1.54)	(1.94)	(2.24)	(2.62)	(2.42)	(2.58)	(2.49)	(2.76)	(9.10)
α_{CAPM}	-1.41	-0.46	-0.24	-0.12	0.00	0.11	0.07	0.12	0.14	0.35	1.76
	(-5.62)	(-2.63)	(-1.59)	(-0.86)	(0.01)	(0.97)	(0.63)	(1.00)	(0.77)	(1.53)	(9.60)
α_{FFC}	-1.31	-0.45	-0.27	-0.10	-0.04	0.07	0.04	0.13	0.17	0.50	1.81
	(-9.61)	(-3.79)	(-2.55)	(-0.99)	(-0.47)	(0.79)	(0.40)	(1.48)	(1.41)	(2.61)	(9.42)
N	134.9	135.0	134.9	135.1	134.7	135.3	134.9	135.0	134.9	135.0	—

Table 3. CFER-adjusted excess returns: Alphas of CFER-sorted portfolios

Entries in Panel A report the intercepts α_{CAPM} and α_{FFC} of the regressions of CFER-adjusted excess returns $R_{t,t+1} - R^0_{t,t+1} - CFER_{t,t+1}$ on a set of risk factor(s) of the CAPM and Carhart (1997) four-factor model, respectively (i.e., equation (20)). On the last trading day of each month t, stocks are sorted in ascending order based on AVE-CM CFER and then value-weighted decile portfolios are formed. We then calculate the average CFER as well as the return in the succeeding month-$(t+1)$ of these portfolios and the spread portfolio to calculate the CFER-adjusted excess return. Entries in Panel B report α_{CAPM} and α_{FFC}, where we eliminate CFER observations below 1st percentile and above 99th percentile point. Entries in Panel C report α_{CAPM} and α_{FFC}, where we form quintile portfolios instead of the decile portfolios. The estimation period spans January 1996 to April 2016 (244 months) for all Panels. t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in the parentheses. The unit of all variables is % per month.

	AVE-CM CFER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Panel A: Decile sort with all available CFER											
α_{CAPM}	0.17	-0.05	0.08	-0.07	0.14	0.15	0.17	-0.04	-0.02	-0.37	-0.55
	(0.94)	(-0.29)	(0.70)	(-0.66)	(1.41)	(1.42)	(1.65)	(-0.38)	(-0.14)	(-1.95)	(-2.31)
α_{FFC}	0.22	-0.08	0.05	-0.05	0.10	0.13	0.17	0.00	0.09	-0.16	-0.39
	(1.44)	(-0.50)	(0.45)	(-0.48)	(1.01)	(1.31)	(1.68)	(0.04)	(0.49)	(-0.79)	(-1.57)
Panel B: Decile sort where CFER below 1st or above 99th percentile are eliminated											
α_{CAPM}	0.02	0.00	0.11	-0.02	0.11	0.12	0.13	0.06	-0.02	-0.33	-0.36
	(0.13)	(0.02)	(1.03)	(-0.16)	(1.18)	(1.12)	(1.26)	(0.52)	(-0.14)	(-1.78)	(-1.57)
α_{FFC}	0.03	-0.02	0.09	0.00	0.08	0.09	0.13	0.08	0.09	-0.16	-0.19
	(0.18)	(-0.12)	(0.91)	(0.05)	(0.80)	(0.94)	(1.32)	(0.79)	(0.52)	(-0.84)	(-0.88)

Panel C: Quintile sort with all available CFER

	AVE-CM CFER-sorted value-weighted quintile portfolios					Spread
	1 (Lowest)	2	3	4	5 (Highest)	5-1
α_{CAPM}	0.00	0.01	0.14	0.08	-0.17	-0.17
	(-0.02)	(0.15)	(1.70)	(1.00)	(-1.29)	(-0.85)
α_{FFC}	-0.01	0.01	0.11	0.09	-0.02	-0.01
	(-0.08)	(0.17)	(1.46)	(1.14)	(-0.14)	(-0.06)

Table 4. Characteristics of AVE-CM CFER-sorted value-weighted decile portfolios

Entries report the average value of various characteristics of decile portfolios as well as the difference between the highest CFER decile portfolio and the lowest CFER decile portfolio. On the last trading day of each month t, stocks are sorted in ascending order based on AVE-CM CFER and then value-weighted decile portfolios are formed. We then calculate the value-weighted average value of characteristics. BAS is the relative bid-ask spread, Amihud is Amihud's (2002) illiquidity measure (multiplied by 1,000 for the sake of readability), SIZE is the natural log of the market equity, S_t is the stock price level, IVOL is the idiosyncratic volatility, beta is the regression coefficient of stock returns on the market portfolio return, RSI is the relative short-interest, ESF is the estimated shorting fee, B/M is the book-to-market ratio, and N is the number of average stocks in each portfolio. See Appendix B for the detailed description of each variable. The data period spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in the parentheses.

	AVE-CM CFER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
CFER	-1.31	-0.53	-0.31	-0.18	-0.09	-0.01	0.07	0.18	0.36	0.93	2.24
	(-15.88)	(-12.34)	(-10.92)	(-9.52)	(-7.03)	(-1.25)	(7.26)	(13.59)	(15.08)	(16.17)	(15.38)
BAS	0.48	0.39	0.35	0.34	0.33	0.31	0.31	0.34	0.37	0.44	-0.04
	(2.67)	(2.51)	(2.14)	(2.31)	(2.15)	(2.18)	(2.25)	(2.34)	(2.28)	(2.69)	(-2.89)
Amihud	5.60	1.84	0.97	0.55	0.37	0.31	0.36	0.55	1.17	3.82	-1.78
	(6.96)	(6.13)	(5.09)	(5.74)	(6.26)	(5.94)	(7.93)	(7.50)	(7.70)	(6.23)	(-4.76)
SIZE	15.34	16.30	16.81	17.14	17.43	17.47	17.46	17.20	16.66	15.76	0.42
	(221.77)	(192.45)	(320.21)	(386.63)	(372.29)	(292.14)	(282.72)	(255.42)	(268.91)	(189.59)	(3.96)
S_t	36.72	49.00	58.69	62.37	68.08	69.36	70.39	60.62	52.92	39.08	2.35
	(23.40)	(23.50)	(18.87)	(20.09)	(22.06)	(22.03)	(16.44)	(18.72)	(18.38)	(15.68)	(1.33)
IVOL	39.53	31.74	28.24	26.37	24.93	24.69	24.89	26.22	29.07	35.21	-4.32
	(18.06)	(13.67)	(10.23)	(10.25)	(9.40)	(9.46)	(9.82)	(10.76)	(13.13)	(12.95)	(-7.30)
Beta	1.20	1.12	1.05	1.02	1.01	1.01	1.03	1.04	1.07	1.16	-0.04
	(53.61)	(79.84)	(132.19)	(86.01)	(69.39)	(59.49)	(72.21)	(102.76)	(102.44)	(55.50)	(-2.04)
RSI	6.19	3.97	2.99	2.52	2.22	2.09	2.19	2.47	3.14	4.28	-1.90
	(19.54)	(30.61)	(46.87)	(39.76)	(35.74)	(22.78)	(19.30)	(21.57)	(32.74)	(29.84)	(-8.41)
ESF	0.57	0.43	0.35	0.30	0.27	0.25	0.26	0.29	0.36	0.47	-0.11
	(13.46)	(8.30)	(8.82)	(8.37)	(6.80)	(8.83)	(9.00)	(8.96)	(9.20)	(9.08)	(-6.52)
B/M	0.53	0.47	0.44	0.43	0.41	0.40	0.40	0.42	0.44	0.48	-0.05
	(13.32)	(19.51)	(22.86)	(19.74)	(13.87)	(13.75)	(13.49)	(13.55)	(16.70)	(16.02)	(-4.30)
N	134.93	135.02	134.89	135.06	134.69	135.25	134.94	135.00	134.91	135.05	—

Table 5. Performance of CFER-sorted portfolios: Bivariate dependent sorts controlling for relative bid-ask spread or SIZE

Entries in Panel A report the result of the bivariate dependent sort, where we first sort stocks based on the relative bid-ask spread (BAS), and then within each group of the BAS level, we further sort stocks into quintile portfolios by the AVE-CM CFER criterion. Rows correspond to the level of the first sorting variable, BAS, and the first to the fifth columns correspond to the level of the second sorting variable,AVE-CM CFER. Sixth to the last columns report the average returns, Fama and French (2015) five-factor alpha, and the average CFER, respectively, of the spread portfolio (the highest CFER portfolio minus the lowest CFER portfolio). Entries in Panel B report the result, where we use SIZE (the log of market equity) as the first sorting variable instead of BAS. The estimation period spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation (HAC-adjusted t-stat). The unit of the average returns and alphas (average CFER) is % per month (per 30-days).

	Ave. returns of AVE-CM CFER-sorted portfolios					Ave. return	α_{FFC}	Ave. CFER
	1 (lowest)	2	3	4	5 (highest)	Spread portfolio (5-1)		
Panel A: Relative bid-ask spread-sorted dependent bivariate sort								
BAS 1	0.11	0.63	0.65	0.76	0.84	0.74	0.86	0.75
(narrowest)	(0.25)	(1.65)	(1.54)	(1.75)	(2.19)	(3.47)	(3.29)	(13.71)
BAS 2	0.31	0.48	0.81	0.70	1.09	0.78	0.69	1.05
	(0.72)	(1.24)	(2.37)	(1.78)	(2.59)	(3.31)	(2.96)	(10.63)
BAS 3	0.41	0.59	0.98	0.93	1.30	0.89	0.93	1.34
	(1.01)	(1.52)	(2.56)	(2.26)	(3.03)	(3.26)	(3.22)	(12.30)
BAS 4	0.14	0.70	0.68	0.85	1.48	1.33	1.48	1.70
	(0.30)	(1.56)	(1.69)	(2.06)	(3.22)	(4.60)	(4.62)	(14.90)
BAS 5	-0.42	0.28	0.85	0.78	1.53	1.95	1.94	2.64
(widest)	(-0.72)	(0.57)	(1.79)	(1.64)	(3.29)	(5.54)	(5.90)	(14.59)
Panel B: Size-sorted dependent bivariate sort								
SIZE 1	-0.62	0.48	0.72	0.96	1.22	1.84	1.79	3.18
(smallest)	(-1.00)	(0.85)	(1.31)	(1.63)	(2.06)	(6.54)	(6.39)	(16.56)
SIZE 2	0.16	0.86	0.85	0.94	1.28	1.12	1.12	1.95
	(0.30)	(1.70)	(1.84)	(2.02)	(2.53)	(4.94)	(4.94)	(14.13)
SIZE 3	0.30	0.78	0.86	0.96	1.26	0.96	1.04	1.46
	(0.66)	(1.83)	(2.06)	(2.33)	(3.07)	(4.82)	(4.86)	(15.77)
SIZE 4	0.70	0.76	0.99	1.20	1.21	0.51	0.57	1.01
	(1.72)	(1.98)	(2.77)	(3.35)	(3.27)	(3.01)	(3.14)	(12.43)
SIZE 5	0.33	0.69	0.78	0.88	0.94	0.61	0.67	0.65
(largest)	(1.03)	(2.52)	(2.48)	(2.96)	(2.89)	(3.50)	(3.65)	(12.64)

Table 6. CFER and firms' and stocks' characteristics: Fama-MacBeth regressions

Entries in Panel A report the results from Fama and MacBeth (1973) regressions of AVE-CM CFER on SIZE (log of market equity), relative bid-ask spread (BAS), idiosyncratic volatility (IVOL), Amihud's (2002) illiquidity measure, and relative short interest (RSI), where we use positive CFER subsamples. Entries in Panel B report the results, where we use negative CFER subsamples. Even though the intercept is included in the regressions, we do not report them due to space limitations. The time-series averages of the estimated coefficients of the cross-sectional regressions are reported. t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in the parentheses. The time-series averages of adjusted R^2 and the number of observations N employed in the cross-sectional regressions are reported in the last two rows of each Panel. The data period spans January 1996 to April 2016 (244 months).

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Positive CFER subsample						
SIZE	-0.11					-0.06
	(-14.46)					(-14.92)
BAS		1.22				0.55
		(4.52)				(6.24)
IVOL			0.78			0.19
			(15.13)			(3.65)
Amihud				17.94		1.38
				(6.98)		(0.67)
RSI					0.85	-0.44
					(9.96)	(-5.04)
adj. R^2	14.3%	10.2%	9.0%	10.3%	0.7%	16.7%
N	579.6	554.5	565.2	565.7	495.6	451.0
Panel B: Negative CFER subsample						
SIZE	0.15					0.05
	(15.49)					(9.72)
BAS		-1.57				-0.92
		(-4.08)				(-4.48)
IVOL			-1.10			-0.32
			(-12.79)			(-7.11)
Amihud				-20.68		-6.13
				(-6.97)		(-4.26)
RSI					-1.57	-0.31
					(-14.17)	(-4.63)
adj. R^2	14.8%	12.6%	12.5%	10.5%	2.8%	19.0%
N	718.5	672.7	694.9	695.2	595.0	528.5

Table 7. Robustness tests: (i) Comparison of methods to estimate CFER, (ii) Removing extreme CFER values

Entries in Panel A report the average return and Carhart (1997) four-factor model alpha of the spread portfolio of CFER-sorted value-weighted decile portfolios, where each column uses one of four estimation methods of CFER. The first row denotes the method of choosing strikes (AVE: taking average across available strikes, ATM: choosing the strike closest to the forward price) and the second row denotes the method of choosing maturities (CM: interpolating traded maturities to construct 30-day constant maturity CFER, CLS: choosing the traded maturity closest to 30 days). Entries in Panel B report the average return and Carhart (1997) four-factor model alpha of the spread portfolio of AVE-CM CFER-sorted value-weighted portfolios. The first column shows the result, where we truncate AVE-CM CFER values at a 1% level, that is, we remove CFER samples below 1st percentile point or above 99th percentile point. The second column reports the result of the modified spread, where we long the second highest CFER portfolio (portfolio 9) and short the second lowest CFER portfolio (portfolio 2). The third column reports the quintile portfolio sort results, and the last column reports the modified spread of the quintile portfolios, where we long the second highest CFER portfolio (portfolio 4) and short the second lowest CFER portfolio (portfolio 2). The estimation period spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation (HAC-adjusted t-stat). The unit of the mean returns and alphas are % per month.

Panel A: Comparison between four estimation methods of CFER				
Strike	AVE		ATM	
Maturity	CM	CLS	CM	CLS
Value-weighted decile spread portfolio				
Average return	1.64	1.56	1.49	1.38
	(5.77)	(5.44)	(5.33)	(4.89)
α_{FFC}	1.86	1.77	1.60	1.51
	(6.56)	(6.20)	(5.55)	(5.33)
Equally-weighted decile spread portfolio				
Average return	1.73	1.56	1.67	1.54
	(9.10)	(8.92)	(9.15)	(8.95)
α_{FFC}	1.81	1.65	1.75	1.62
	(9.42)	(9.18)	(9.12)	(9.21)

Panel B: Mitigating effect of extreme CFER samples				
	Truncated decile sort (VW)		Quintile sort (VW)	
	Spread (10-1)	Spread (9-2)	Spread (5-1)	Spread (4-2)
Average return	1.43	0.92	1.11	0.43
	(6.08)	(4.19)	(5.59)	(3.37)
α_{FFC}	1.65	0.93	1.29	0.43
	(7.05)	(3.77)	(5.65)	(3.27)

Table 8. Bivariate dependent sort on CFER: Controlling for previous month return

Entries report the result of the bivariate dependent sort, where we first sort stocks based on the previous month return, $R_{t-1,t}$, and then within each group of the bid-ask spread level, we further sort stocks into quintile portfolios by the AVE-CM CFER criterion. Rows correspond to the level of the first sorting variable, the previous month return $R_{t-1,t}$, and the first to the fifth columns correspond to the level of the second sorting variable, AVE-CM CFER. The sixth to last columns report the average return, α_{FFC}, and the average CFER of the CFER-sorted spread portfolios, respectively. All returns are value-weighted returns. The estimation period spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation (HAC-adjusted t-stat). The unit of the mean returns and alphas are % per month.

	Ave. returns of AVE-CM CFER-sorted portfolios					Ave. return	α_{FFC}	Ave. CFER
	1 (lowest)	2	3	4	5 (highest)	Spread portfolio (5-1)		
$R_{t,-1,t}$ 1	-0.51	0.34	1.15	0.44	1.28	1.79	2.02	1.72
(lowest)	(-0.78)	(0.65)	(2.45)	(0.86)	(1.99)	(4.87)	(5.02)	(13.33)
$R_{t,-1,t}$ 2	0.50	0.76	1.04	1.04	1.30	0.80	0.90	1.24
	(1.10)	(2.23)	(2.79)	(2.98)	(3.51)	(2.83)	(2.83)	(13.69)
$R_{t,-1,t}$ 3	0.31	0.35	0.78	1.16	1.44	1.14	1.22	1.12
	(0.82)	(1.06)	(2.44)	(3.71)	(3.96)	(4.39)	(4.40)	(14.42)
$R_{t,-1,t}$ 4	0.58	0.51	0.81	0.76	0.97	0.39	0.52	1.11
	(1.53)	(1.68)	(2.59)	(2.33)	(2.75)	(1.44)	(1.83)	(15.30)
$R_{t,-1,t}$ 5	0.00	0.41	0.58	0.93	0.85	0.85	0.96	1.52
(highest)	(-0.00)	(0.93)	(1.51)	(2.21)	(2.04)	(2.88)	(3.15)	(18.81)

Table 9. Robustness tests: Non-synchronicity, Low stock price level, and NYSE breakpoint

Entries in Panel A report the average return and Carhart (1997) four-factor model alpha of the spread portfolio of AVE-CM CFER-sorted value-weighted decile portfolios, where the returns are calculated as the open-to-close return. The open-to-close return is the return from the open price on the first trading date after the portfolio formation in month-t to the close price of the end of month-$t+1$. Entries in Panel B report the average return and α_{FFC} of the AVE-CM CFER-sorted value-weighted decile portfolios, where we discard stocks whose price level is below \$10. Entries in Panel C report the the average return and α_{FFC} of the AVE-CM CFER-sorted value-weighted decile portfolios, where we calculate decile portfolios' breakpoints based on NYSE stocks only. The estimation period spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation (HAC-adjusted t-stat). The unit of the mean returns and alphas are % per month.

	AVE-CM CFER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Panel A: Open-to-close return (non-synchronicity)											
Ave. return	-0.21	0.22	0.52	0.48	0.77	0.87	0.97	0.90	1.13	1.39	1.60
	(-0.43)	(0.57)	(1.52)	(1.59)	(2.51)	(2.77)	(3.16)	(2.66)	(3.12)	(3.21)	(5.58)
α_{FFC}	-1.14	-0.63	-0.28	-0.25	-0.01	0.10	0.23	0.16	0.42	0.69	1.83
	(-6.73)	(-3.80)	(-2.42)	(-2.41)	(-0.14)	(0.99)	(2.27)	(1.30)	(2.40)	(3.20)	(6.40)
Panel B: Eliminating stocks whose price is below \$10											
Ave. return	-0.09	0.28	0.49	0.52	0.79	0.91	0.89	0.98	1.05	1.26	1.35
	(-0.18)	(0.79)	(1.49)	(1.75)	(2.62)	(2.82)	(2.99)	(2.95)	(3.00)	(3.23)	(5.79)
α_{FFC}	-1.03	-0.51	-0.29	-0.20	0.01	0.10	0.17	0.23	0.35	0.55	1.57
	(-5.07)	(-3.27)	(-2.92)	(-2.03)	(0.07)	(0.99)	(1.68)	(2.15)	(2.18)	(3.15)	(5.96)
N	122.0	122.2	122.1	122.2	121.8	122.3	122.1	122.2	122.1	122.1	—
Panel C: NYSE breakpoints											
Ave. return	-0.02	0.48	0.51	0.60	0.80	0.90	0.88	1.11	0.93	1.33	1.35
	(-0.04)	(1.38)	(1.51)	(2.01)	(2.58)	(2.79)	(2.96)	(3.48)	(2.66)	(3.26)	(5.33)
α_{FFC}	-0.95	-0.34	-0.27	-0.13	0.00	0.10	0.16	0.36	0.18	0.63	1.58
	(-4.92)	(-2.56)	(-2.28)	(-1.19)	(-0.04)	(0.99)	(1.45)	(3.26)	(1.45)	(3.25)	(5.85)
N	182.0	136.6	124.0	118.7	115.3	115.3	117.3	122.1	134.0	181.1	—

Table 10. Robustness test: Sub-sample analysis

Entries in Panels A and B report the average return and Carhart (1997) four-factor model alpha of the spread portfolio of AVE-CM CFER-sorted value-weighted decile portfolios over January 1996 to December 2006 and January 2007 to April 2016, respectively. t-statistics adjusted for heteroscedasticity and autocorrelation and reported in the parentheses. The unit of all variables is % per month.

	AVE-CM CFER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Panel A: Sub-sample, January 1996–December 2006											
Average return	-0.19	0.30	0.57	0.49	0.89	0.99	1.13	0.82	1.42	1.76	1.95
	(-0.31)	(0.60)	(1.33)	(1.19)	(2.25)	(2.41)	(2.77)	(1.90)	(2.79)	(3.04)	(5.02)
α_{FFC}	-1.20	-0.71	-0.36	-0.33	-0.02	0.16	0.33	-0.02	0.74	1.20	2.41
	(-5.48)	(-2.96)	(-1.87)	(-2.18)	(-0.12)	(1.07)	(1.99)	(-0.12)	(2.54)	(3.84)	(6.38)
Panel B: Sub-sample, January 2007–April 2016											
Average return	-0.17	0.15	0.51	0.50	0.66	0.77	0.81	1.03	0.84	1.10	1.27
	(-0.21)	(0.24)	(0.94)	(1.07)	(1.38)	(1.57)	(1.72)	(1.97)	(1.59)	(1.69)	(3.24)
α_{FFC}	-0.87	-0.49	-0.16	-0.10	-0.01	0.09	0.14	0.34	0.18	0.35	1.22
	(-3.36)	(-2.03)	(-0.99)	(-0.78)	(-0.05)	(0.97)	(1.16)	(2.44)	(1.07)	(1.56)	(3.12)

Table 11. Predictive power of CFER: Fama-MacBeth regressions

Entries report the results from Fama and MacBeth (1973) regressions of stock returns on AVE-CM CFER, market beta, SIZE (log of market equity), log of book-to-market (B/M), Momentum ($R_{t-12,t-1}$), previous month return $R_{t-1,t}$, idiosyncratic volatility (IVOL), profitability (operational profit to book equity), investment (asset growth rate), Amihud's (2002) illiquidity measure, relative bid-ask spread (BAS) and turnover rate. See Appendix B for detailed definition of these variables. The time-series averages of the estimated coefficients of the cross-sectional regressions are reported. t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in the parentheses. The time-series averages of adjusted R^2 and the observation number N of cross-sectional regressions are reported in the last two rows. Columns (1), (2), (3) report the results using all samples from January 1996 to April 2016. Columns (4) and (5) report the results using only NYSE/Amex and NASDAQ stocks, respectively. Columns(6) and (7) report the results using only the observations with non-negative and negative AVE-CM CFER, respectively. Columns (8) and (9) report the results using only the observation over 1996-2006 and 2007-2016, respectively.

	All sample			NYSE/ Amex	NASDAQ	$CFER \geq 0$	$CFER < 0$	1996–2006	2007–2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CFER	0.62	0.39	0.40	0.53	0.31	0.46	0.46	0.41	0.38
	(7.78)	(5.60)	(5.60)	(4.12)	(3.23)	(2.78)	(4.01)	(4.14)	(3.70)
Beta		-0.03	-0.02	-0.02	-0.06	0.19	-0.01	0.19	-0.26
		(-0.12)	(-0.07)	(-0.08)	(-0.20)	(0.63)	(-0.03)	(0.48)	(-0.64)
SIZE		-0.11	-0.12	-0.14	0.01	-0.06	-0.11	-0.12	-0.12
		(-1.92)	(-1.95)	(-2.22)	(0.12)	(-0.88)	(-1.78)	(-1.23)	(-1.71)
log(BM)		0.11	0.11	0.11	0.15	0.14	0.08	0.32	-0.13
		(1.12)	(1.14)	(1.28)	(1.36)	(1.24)	(0.85)	(2.29)	(-1.19)
$R_{t-12,t-1}$		-0.02	-0.01	0.09	-0.11	-0.05	-0.04	0.24	-0.31
		(-0.05)	(-0.03)	(0.22)	(-0.38)	(-0.14)	(-0.10)	(0.77)	(-0.47)
$R_{t-1,t}$		-1.12	-1.26	-0.53	-1.78	-1.55	-0.88	-2.50	0.21
		(-1.58)	(-1.81)	(-0.64)	(-2.47)	(-1.91)	(-1.18)	(-2.91)	(0.20)
IVOL		-0.01	0.00	-0.02	0.01	0.00	0.00	0.00	-0.01
		(-1.47)	(-0.51)	(-2.07)	(0.87)	(-0.27)	(-0.75)	(0.16)	(-1.10)
Profitability		0.27	0.28	0.22	0.27	0.37	0.42	0.53	0.00
		(2.07)	(1.92)	(1.73)	(0.88)	(2.00)	(2.35)	(2.12)	(-0.00)
Investment		-0.33	-0.33	-0.46	-0.25	-0.39	-0.28	-0.34	-0.32
		(-3.76)	(-3.64)	(-2.98)	(-2.48)	(-2.64)	(-2.60)	(-3.24)	(-2.01)
Amihud			-14.62	-2.51	0.92	-34.98	-17.24	-2.77	-28.59
			(-2.43)	(-0.09)	(0.12)	(-2.06)	(-1.08)	(-0.45)	(-2.68)
BAS			0.44	0.47	-0.66	0.52	0.70	0.10	0.84
			(0.62)	(0.53)	(-0.66)	(0.44)	(0.71)	(0.16)	(0.62)
Turnover			-0.12	0.18	-0.26	-0.36	-0.08	-0.11	-0.14
			(-0.72)	(0.86)	(-0.94)	(-1.82)	(-0.48)	(-0.37)	(-1.27)
Intercept	0.88	2.84	2.92	3.32	1.09	2.17	2.72	3.05	2.76
	(2.17)	(3.03)	(2.83)	(3.00)	(0.52)	(1.85)	(2.56)	(1.84)	(2.29)
Ave. adj. R^2	0.2%	9.0%	9.2%	10.7%	7.6%	10.1%	9.9%	10.4%	7.8%
Ave. N	1322.7	1008.5	940.2	548.9	401.7	430.3	513.7	775.7	1134.0

Table 12. Predictive power of CFER, IVS, and DOTS

Entries report the average return and five risk-adjusted returns with respect to the CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, Fama and French (2015) five-factor model, and Stambaugh and Yuan (2017) mispricing-factor model of the spread portfolio of AVE-CM CFER-sorted value-weighted decile portfolios, IVS-sorted value-weighted decile portfolios, and DOTS-sorted value-weighted decile portfolios. The analysis spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in parentheses. The unit of all variables is % per month.

	Average return	α_{CAPM}	α_{FF3}	α_{FFC}	α_{FF5}	α_{SY}
CFER-sorted	1.64	1.70	1.78	1.86	1.58	1.70
	(5.77)	(5.91)	(6.36)	(6.56)	(5.63)	(5.21)
IVS-sorted	1.17	1.23	1.30	1.38	1.14	1.25
	(4.90)	(4.76)	(4.94)	(5.24)	(4.64)	(4.25)
DOTS-sorted	1.45	1.42	1.46	1.47	1.31	1.28
	(5.61)	(4.93)	(4.99)	(4.98)	(4.70)	(4.19)

Table A.1. Portfolio sort results based on the fully-estimated CFER: the embedded leverage model and the margin constraints model

Entries report the average return and the five risk-adjusted returns (α's) with respect to the CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, Fama and French (2015) five-factor model, and Stambaugh and Yuan (2017) mispricing-factor model, of the spread portfolio of the CFER-sorted value-weighted decile portfolios. The first two rows reports the results based on the baseline AVE-CM CFER, which ignores U_t for the sake of expediting the comparison. Panel A shows the results based on the fully-estimated CFER, where U_t is estimated based on the embedded leverage model. Panel B shows the results based on the fully-estimated CFER, where U_t is estimated based on the margin constraints model. For the margin constraints model, we consider nine alternative fully-estimated AVE-CM CFER. Each one of the nine alternative CFER is characterized by the assumption on $R^0_{t,+1}\lambda^{mc}_t$ and the assumption on the reference point of the option expensiveness s, which determines the value of $E_t(K)$. The analysis spans January 1996 to April 2016 (244 months). t-statistics are adjusted for heteroscedasticity and autocorrelation and reported in the parentheses. Figures in the square brackets show the t-statistics of the difference between the baseline result and each one of the fully-estimated CFER-sorted results. The unit of all variables is % per 30 days.

		Ave. Ret	α_{CAPM}	α_{FF3}	α_{FFC}	α_{FF5}	α_{SY}
Panel A: Embedded leverage model							
Baseline result		1.64	1.70	1.78	1.86	1.58	1.70
		(5.77)	(5.91)	(6.36)	(6.56)	(5.63)	(5.21)
Fully-estimated		1.54	1.61	1.66	1.75	1.41	1.56
		(6.22)	(6.37)	(6.30)	(6.71)	(5.98)	(5.63)
		[-0.60]	[-0.53]	[-0.74]	[-0.66]	[-0.95]	[-0.76]
Panel B: Margin constraints model							
$R^0_{t,t+1}\psi =$	$s = 0.00$	1.58	1.64	1.75	1.83	1.49	1.63
10% per year		(5.28)	(5.30)	(5.95)	(6.16)	(5.45)	(4.84)
		[-0.56]	[-0.50]	[-0.27]	[-0.23]	[-0.72]	[-0.42]
	$s = 0.01$	1.61	1.66	1.77	1.85	1.50	1.65
		(5.42)	(5.36)	(5.99)	(6.25)	(5.56)	(4.94)
		[-0.25]	[-0.31]	[-0.11]	[-0.08]	[-0.55]	[-0.26]
	$s = 0.02$	1.73	1.79	1.89	1.97	1.65	1.78
		(5.58)	(5.49)	(6.03)	(6.35)	(5.66)	(5.07)
		[0.82]	[0.73]	[0.84]	[0.68]	[0.45]	[0.42]
$R^0_{t,t+1}\psi =$	$s = 0.00$	1.57	1.63	1.71	1.76	1.49	1.56
5% per year		(5.46)	(5.55)	(6.14)	(6.09)	(5.54)	(5.12)
		[-0.94]	[-0.99]	[-0.91]	[-1.03]	[-0.98]	[-1.12]
	$s = 0.01$	1.63	1.69	1.79	1.85	1.53	1.65
		(5.52)	(5.42)	(5.97)	(6.28)	(5.46)	(4.95)
		[-0.10]	[-0.12]	[0.07]	[-0.04]	[-0.44]	[-0.30]
	$s = 0.02$	1.69	1.76	1.86	1.93	1.62	1.76
		(5.54)	(5.61)	(6.15)	(6.43)	(5.63)	(5.20)
		[0.55]	[0.59]	[0.72]	[0.49]	[0.27]	[0.34]
$R^0_{t,t+1}\psi =$	$s = 0.00$	1.60	1.66	1.74	1.78	1.49	1.56
Time-varying		(5.50)	(5.65)	(6.20)	(6.18)	(5.42)	(5.09)
		[-0.64]	[-0.69]	[-0.70]	[-0.86]	[-1.06]	[-1.14]
	$s = 0.01$	1.60	1.66	1.74	1.78	1.50	1.57
		(5.54)	(5.70)	(6.24)	(6.19)	(5.46)	(5.15)
		[-0.58]	[-0.63]	[-0.65]	[-0.87]	[-0.96]	[-1.09]
	$s = 0.02$	1.64	1.71	1.79	1.82	1.55	1.62
		(5.59)	(5.74)	(6.24)	(6.16)	(5.55)	(5.20)
		[0.10]	[0.10]	[0.10]	[-0.42]	[-0.39]	[-0.64]