The Contribution of Mispricing to Expected Returns*

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February 16, 2018

Abstract

We examine the contribution of stock mispricing to expected returns (CMER) within a financial intermediary equilibrium asset pricing model, where the market price of the stock deviates from its fundamental price due to frictions in the stock market. The stock's expected return consists of two parts: CMER and the risk-premium term determined by the covariance between the financial intermediaries' marginal utility of wealth and the stock return. We derive a model-free formula which enables us to compute CMER from equity options' prices. Our approach makes no assumptions on the source and dynamics of mispricing and it does not rely on a specific asset pricing model. The model predicts that CMER is positively related to future stock returns, CMER is a model-free alpha, and the variation of CMER is larger when transaction costs are larger. We document that these predictions hold for a large cross-section of U.S. common stocks. We also show that CMER relates to other popular option-implied measures of mispricing and hence we explain theoretically why these measures have been found to predict stock returns.

JEL classification: C13, G12, G13

Keywords: Alpha, Asset pricing, Frictions, Implied volatility spread, Mispricing

*We would like to thank Renato Faccini, Marcelo Fernandes, Elise Gourier, Tatsuro Senga, Roman Sustek, Dimitri Vayanos, and Konstantinos Zachariadis for useful discussions and comments. All remaining errors are the sole responsibility of the authors.

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1 Introduction

Frictions on trading stocks (e.g., margins, short selling constraints, transaction costs) may incur stock mispricing defined as the difference between the market and the fundamental stock price (Shleifer and Vishny, 1997). In such a case, stock expected returns will reflect the effect of mispricing, in addition to compensation for exposure to risk factors. We make four contributions to the growing literature on asset pricing in the presence of mispricing. We take a general approach by making the minimum number of assumptions to (i) examine how stock mispricing shows up in an asset pricing setting, (ii) estimate the effect of mispricing to expected stock returns, (iii) investigate the testable predictions, and (iv) use our setting to provide a theoretical explanation about why certain option-based measures of mispricing have been previously found to predict stock returns.

First, we derive a financial intermediary equilibrium asset pricing model in the presence of stock mispricing caused by stock market frictions. We assume that there are two types of representative traders, the "market-maker" (i.e., the financial intermediary) who is the liquidity provider and the "end-user" (e.g., retail investor) whose demand is exogenously given. In this model, an additional term, the *contribution of mispricing to expected returns* (CMER), appears on top of the covariance risk premium term:

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

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 financial intermediary under asset's mispricing; $m_{t,t+1}^*$ is defined via the first-order condition of the financial intermediary's consumption-portfolio choice problem, where the market frictions impose constraints on her portfolio allocations.[1]

[1] Note that the decomposition of expected returns in equation (1) arises because of the way we define mispricing which is distinct from papers where mispricing is defined as the difference between two prices of the same asset calculated with two different respective IMRS; one is the market-maker's IMRS that is affected by demand pressure from the end-user, and the other is the representative agent's IMRS, where the effect of demand pressure is absent (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)). Our definition of mispricing is different; we only

Equation (1) shows that CMER can be viewed as the *true* alpha, i.e., it is a part of the expected excess return, which cannot be explained by the covariance risk premium term; the latter is calculated as the covariance between the asset return and the *true* (i.e., model-free) IMRS, which is proportional to the financial intermediary's marginal utility of wealth. Therefore, CMER does not represent compensation for risk and hence it should not be interpreted as a priced factor. Rather, it reflects the stock's out-/under-performance due to the existence of market frictions. We show that $CMER_{t,t+1}$ is proportional to the expected *change* in stock's mispricing over the period $[t, t+1]$. Therefore, $CMER_{t,t+1}$ does not reflect the level of mispricing, i.e., whether the stock is currently overpriced or underpriced. Our model does not pin down the sign of CMER, rather it lets it to be determined empirically. Our theoretical model yields three testable predictions. First, CMER predicts future excess returns. Second, equation (1) implies the intercept of the regression of "CMER-adjusted excess returns" $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$ on a set of risk factors that proxy the covariance risk premium term should be zero. Third, we extend He and Modest (1995) and show that for any given stock, the range of possible CMER values increases as the size of transaction costs increases.

Our second contribution has to do with providing a simple formula to calculate CMER. The formula uses the market prices of a pair of European call and put options with the same strike price and maturity and their underlying stock price. CMER is computed as the *scaled* difference between the European call market price and the price of a synthetic European call obtained in the case where the put-call parity would hold. Hence, intuitively, a non-zero CMER conveys information about stock mispricing because it reflects the violation of put-call parity due to stock mispricing.[2] Our asset pricing model and the formula to estimate CMER are model-free in the sense that we make no assumptions on the source and time series dynamics of mispricing, nor on the functional form of IMRS. Most interestingly, our model-free formula for CMER enables us to calculate the *true* alpha and hence it bypasses the problem of estimating

consider the market-maker's IMRS that is affected by demand pressure, and the mispricing is a result of binding constraints on asset allocations like in Gârleanu and Pedersen (2011). Our definition yields the decomposition of expected returns in equation (1) and subsequently enables the derivation of a formula to estimate CMER.

[2]A non-zero CMER indicates that the law of one price (i.e., assets with identical payoffs should have the same price) does not hold. Note that even though the law of one price does not hold, our model is arbitrage-free because the presence of frictions does not allow executable arbitrage strategies to exist.

alpha with respect to a specific asset pricing model which may be mis-specified.

Third, we estimate CMER for a large cross-section of U.S. common stocks over January 1996 to April 2016. We find that CMER is sizable; it takes both positive and negative values, ranging from -14% to 11% per year in a 5th to 95th percentile range. We confirm the three theoretical predictions of the model. We document that CMER predicts stock returns cross-sectionally. We find that a long-short portfolio of the CMER-sorted value-weighted decile portfolios, where we long the portfolio of stocks with the highest CMER and short the portfolio of the lowest CMER, yields a positive average return of 164 bps per month (19.7% per year), which is statistically significant (t-stat: 5.76). Risk-adjusted returns with respect to standard asset pricing models are also economically and statistically significant. For example, Carhart (1997) four-factor model's alpha of the long-short portfolio is 186 bps per month (22.3% per year) and its t-statistic is 6.56. These results document that mispricing contributes to U.S. stocks' expected returns. Our findings are robust to non-synchronous trading in the stock and equity option markets, the portfolio construction method (equally- and value-weighted portfolios), possible outliers in the estimated CMER and over alternative time periods. In line with the model's second prediction, we find that when we regress the CMER-adjusted excess return (defined as the excess return minus the estimated CMER) on a set of risk-factors employed in standard asset pricing models, the intercepts of CMER-sorted portfolios and that of the spread portfolio are insignificant. In line with the third theoretical prediction, we find that the variation of CMER is greater for stocks which are subject to larger market frictions and it increases during market distress periods.

Fourth, we establish the theoretical relation between CMER and three option-implied measures which have also been documented to predict stock returns cross-sectionally: Manaster and Rendleman's (1982) implied stock price, the implied volatility spread (IVS, i.e., the difference between call and put implied volatilities) (e.g., Bali and Hovakimian, 2009, Cremers and Weinbaum, 2010), and Goncalves-Pinto et al.'s (2017) DOTS measure constructed from the stock price implied by the put-call parity. These measures do not rely on a formal definition of the fundamental price, rather they are based on the implicit assumption that the asset price implied from market option prices proxies the fundamental price and that IVS reflects expectations on the future direction of stock prices. Instead, we found CMER theoretically by setting the fundamental price and stock mispricing within a formal asset pricing model. Hence, the fact that we establish a relation between CMER and these three measures allows us to explain theoretically why these measures have been found to predict stock returns. In particular, we show that (i) Manaster and Rendleman's (1982) measure coincides with the discounted value of CMER only in the case where the stock return follows a normal distribution under the risk-neutral probability measure, (ii) IVS is approximately proportional to CMER once the former is scaled by the sensitivity of the option's price to volatility (vega), and (iii) DOTS equals the sum of the discounted value of CMER and an additional term that depends on the early exercise premium of the call and put American options. Given that CMER measures the expected change in mispricing, the derived relations show that Manaster and Rendleman's (1982) and Goncalves-Pinto et al.'s (2017) measures are a function of the expected *change* in mispricing rather than the *level* of mispricing as commonly believed. The theoretical relations between CMER and the option-implied measures imply that CMER should perform at least as well as the other measures as a cross-sectional predictor of stock returns. We verify this testable hypothesis empirically.

Our study contributes to four streams of literature. The first is the growing literature on asset pricing models with mispricing caused by 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 and associated mispricing 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)), margin and leverage constraints (Frazzini and Pedersen (2014)) and exclusion of strategies with unlimited losses (Jarrow (2016)). Another strand of this literature develops asset pricing models by using a reduced form model to model mispricing (e.g., Brennan and Wang (2010) and Hou et al. (2016)). These models make no assumption on the source of mispricing yet, they make assumptions on the dynamics of mispricing and the specification of the IMRS to estimate the mispricing term.[3]

[3]Brennan and Wang (2010) assume that the logarithm of mispricing follows a zero-mean first-order autore-

Our paper is closely related to Brennan and Wang (2010) and Hou et al. (2016) in that we do not specify the source of mispricing either. However, we make no assumptions neither on the dynamics of mispricing nor on the IMRS to derive our asset pricing model (equation (1)) and the formula to estimate CMER. Our model also differs in that it is agnostic about the sign of the contribution of mispricing to expected returns and it lets it to be determined by the data. Instead, Brennan and Wang (2010), and Hou et al.'s (2016) baseline model find that their mispricing term contributes positively to expected returns. In Section 5, we show that this is due to their assumptions on the process that the mispricing term follows over time. Our paper also complements studies which find that the severity of constraints (Hou and Moskowitz (2005)) and the uncertainty regarding future constraints (Engelberg et al. (2017)) affect stocks' returns.

Our research is also pertaining to studies that investigate the informational content of market option prices to predict future stock returns (see e.g., Xing et al. (2010), Yan (2011), Chang et al. (2013), Conrad et al. (2013), An et al. (2014), Stilger et al. (2017), and Giamouridis and Skiadopoulos (2011) and Christoffersen et al. (2013) for reviews); their motivation is that market option prices are formed by informed traders to exploit the sophistication and leverage encountered in option products and hence information is first revealed in the option market and subsequently diffuses to the stock market (Easley et al. (1998)). In particular, given our formula to estimate CMER, our paper is related to studies which document that measures which capture the violation of put-call parity (e.g., Ofek et al. (2004), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Muravyev et al. (2016)) and option-implied stock prices (Manaster and Rendleman (1982), Goncalves-Pinto et al. (2017)) forecast future stock returns. We complement this strand of research by proposing a new option-implied measure CMER to predict stock returns, which is derived under a formal asset pricing model. Moreover, we establish the relation of CMER to the above option-implied measures and thus we provide a theoretical explanation to why these measures have been documented to predict future stock returns.

gressive process and the fundamental return is given by Fama and French (1993) three-factor model. In their baseline analysis, Hou et al. (2016) assume that mispricing follows an independently distributed process and observed returns are serially uncorrelated.

Our paper is also related to Stambaugh et al. (2015), who sort individual stocks into portfolios based on their "alpha" proxied by the average ranking of each stock across eleven anomalies. We also sort stocks into portfolios according to CMER, which is the true alpha since there is no need to assume a specific asset pricing models nor employ specific anomaly variables.

Finally, our study is related to the growing literature on financial intermediaries and asset pricing. Financial intermediaries (e.g., major investment banks) account for most of the trading volume in markets and hence they could be regarded as the marginal investor in lieu of the household; the latter is considered to be the marginal investor in the standard representative agent models. Adrian et al. (2014) and He et al. (2017) find that the financial intermediaries' marginal utility of wealth serves as a pricing kernel for a broad cross-section of financial assets. Our theoretical model lies in this strand of literature because the covariance risk premium is determined by the financial intermediaries' IMRS, which is proportional to their marginal utility of wealth. On the other hand, CMER, which is a part of the expected return, is not attributed to the risk-premium that financial intermediaries demand, yet it plays an important role in explaining the cross-section of individual equities' returns.

The rest of this paper is organized as follows. In Section 2, we provide the asset pricing model under mispricing and the model-free formula to proxy CMER. We also discuss the testable predictions of the model. Section 3 describes the data we use in the empirical analysis, and the way we implement our formula to compute CMER. In Section 4, we conduct a portfolio analysis to test the testable predictions of the model. In Section 5, we discuss the relation between CMER and other option-implied mispricing measures proposed by the previous literature. Section 6 concludes.

2 Theoretical framework

2.1 Mispricing and the intertemporal marginal rate of substitution

In this section, we derive an equilibrium asset pricing model that takes the existence of mispricing in asset prices into account. We consider a market where there is a risky asset (the stock), the risk-free bond, and European call and put options written on the stock. We assume that mispricing exists in the stock market; in Appendix C, we also consider the case where mispricing exists in both the stock and option markets.

We assume that the time horizon is finite and discrete, indexed by $t = 0, 1, 2, \ldots, T$. Let $R^0_{t,t+1}$ denote the gross return of the one-period risk-free bond from time t to $t+1$. We denote the stock price by S_t and its dividend payment at time t by D_t. We also assume that on each date t, there are one-period European call and put options written on the stock maturing at time $t+1$. We assume options are 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 are two types of representative traders, the "market-maker" and the "end-user." The market-maker sets her optimal consumption and asset allocations by maximizing her expected lifetime utility. On the other hand, we follow Gârleanu et al. (2009) to assume that the end-user's demand for financial assets is exogenously given. These assumptions are in line with recent models on frictions where the "focus is on the frictions and behavior of intermediaries" and end-user is not "central to the vision" (Cochrane 2011, page 1069).

Let θ^0_t, θ^S_t, $\theta^c_t(K)$ and $\theta^p_t(K)$ be the market-maker'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 market-maker 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 $\mathbb{E}^{\mathbb{P}}_t$ is the conditional expectation under the physical (real world) measure $\mathbb{P}$ given the information up to time t, β is the subjective discount factor, $u(c)$ is the time-separable utility function. The market-maker 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 the market-maker's wealth at time t, W_t, changes over time as follows:

$$W_{t+1} = \theta^0_t R^0_{t,t+1} + \theta^S_t (S_{t+1} + D_{t+1}) + \sum_{K \in \mathcal{K}_t} \left[\theta^c_t(K)(S_{t+1} - K)^+ + \theta^p_t(K)(K - S_{t+1})^+ \right], \tag{3}$$

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

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

In equations (3)–(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 $t+1$. Finally and most importantly, to introduce mispricing, we assume that frictions exist. These frictions are incurred by the existence of market constraints on the portfolio allocation of the market-maker. Even though we do not specify the types of frictions, we assume that there are L types of constraints on portfolio allocation of the market-maker:

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

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

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

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

$$S_t = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* (S_{t+1} + D_{t+1})] + \sum_{l=1}^{L} \lambda_t^l \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^S}, \tag{7}$$

where $m_{t,t+1}^* = \beta V'(W_{t+1})/u'(c_t)$ 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).[4] Equation (7) shows that if some of constraints are binding, then the current stock price deviates from the IMRS-discounted expected future cum-dividend stock price. On the other

[4]Dividing the both sides of equation (7) by S_t 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 in the case of markets with frictions due to the Lagrange multipliers term; this result has also been derived by He and Modest (1995). Note also that the standard envelop condition $u'(c_t) = V'(W_t)$ does not necessarily hold in general in our model. Indeed, the envelop theorem for constrained maximization problem is given by $V'(W_t) = u'(c_t) \left(1 + \sum_{l=1}^{L} \lambda_t^l (\partial g_t^l / \partial W_t)\right)$.

hand, equation (7) boils down to the first-order condition of the standard frictionless portfolio-consumption problem in the case where there are no frictions.

We solve equation (7) iteratively and use the law of the iterated conditional expectations to obtain,

$$S_t = \mathbb{E}_t^{\mathbb{P}}\left[\sum_{j=t+1}^{T} m_{t,j}^* D_j\right] + \sum_{l=1}^{L} \lambda_t^l \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^S} + \sum_{j=t+1}^{T} \mathbb{E}_t^{\mathbb{P}}\left[m_{t,j}^* \left(\sum_{l=1}^{L} \lambda_j^l \frac{\partial g_t^l(\boldsymbol{\theta}_j)}{\partial \theta_j^S}\right)\right], \tag{8}$$

where

$$m_{t,j}^* = \beta^{j-t} \frac{V'(W_{t+1})}{u'(c_t)} \times \ldots \frac{V'(W_j)}{u'(c_{j-1})} \tag{9}$$

is the multi-period IMRS. Equation (8) shows that the current stock price is the sum of the expected value of the future dividend payments discounted by IMRS, and the additional two terms which are functions of the Lagrange multipliers of the constraints, λ^l. Given equation (8), we define the fundamental price of the stock, F_t, as the first term in the right hand side of equation (8), i.e.,

$$F_t = \mathbb{E}_t^{\mathbb{P}}\left[\sum_{j=t+1}^{T} m_{t,j}^* D_j\right], \tag{10}$$

and we define stock mispricing M_t at time t as the difference between the stock price given by equation (8) and the fundamental stock price, $M_t := S_t - F_t$. In other words, M_t represents the deviation of the stock price from the expected future dividends discounted by the IMRS. Such a deviation can occur when some of the constraints on the portfolio allocation (market frictions, given by equation (5)), are binding today or are expected to be binding in the future as equation (8) shows.

We assume that the risk-free bond market and the option market are frictionless, i.e., any one of L constraint functions $g_t^l(\boldsymbol{\theta}_t)$ does not depend on θ_t^0, $\theta_t^c(K)$ and $\theta_t^p(K)$. In Appendix C, we empirically demonstrate that our empirical findings do not qualitatively change even when we relax the frictionless option market assumption.

Finally, a remark on the definition of the fundamental price is in order. Our definition of the fundamental price does *not* coincide with the hypothetical asset price that would prevail in the frictionless market. This is because the discount rate, IMRS, is a function of the consumption and wealth, which are determined by the market-maker's constrained maximization problem. In other words, our definition of the fundamental price turns off only the direct effect of market frictions on asset prices as this is reflected by the shadow prices of the constraints, yet the IMRS of the financial intermediary per se is derived under the market with frictions. This is in line with Gârleanu and Pedersen's (2011) margin CCAPM, where the covariance risk premium term is defined as the covariance between the asset return and the consumption growth, the latter being determined by the margin-constrained optimization problem.

2.2 The asset pricing model with mispricing

The following Theorem provides the asset pricing model with stock mispricing, that is, how the stock's expected excess return $\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}] - R_{t,t+1}^0$, where $R_{t,t+1} = (S_{t+1} + D_{t+1})/S_t$ is the stock return, is determined when stock mispricing exists.

Theorem 2.1 (Asset pricing model with mispricing) *Under stock mispricing, the following asset pricing model holds:*

$$\mathbb{E}_t^{\mathbb{P}}[R_{t,t+1}] - R_{t,t+1}^0 = CMER_{t,t+1} - \frac{Cov_t^{\mathbb{P}}(m_{t,t+1}^*, R_{t,t+1})}{\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*]}, \tag{11}$$

where $CMER_{t,t+1}$ is the contribution of the mispricing to the expected return from t to $t+1$, defined as

$$CMER_{t,t+1} = \frac{R_{t,t+1}^0}{S_t} \mathbb{E}_t^{\mathbb{P}}\left[m_{t,t+1}^* M_{t+1} - M_t\right]. \tag{12}$$

Proof: See Appendix A.1. □

We can interpret CMER in three ways. First, equation (12) shows that CMER reflects the scaled expected *change* in stock mispricing from time t to $t+1$, rather than the current *level* of stock mispricing.[5] The change in mispricing, rather than the level of mispricing, appears in the

[5] In the case where there are frictions in the risk-free bond market, an additional term $1/\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*] - R_{t,t+1}^0$ appears in the definition of CMER (equation (12)). However, this additional term is common across all individual stocks and hence it does not affect our subsequent tests of CMER as a cross-sectional predictor of stock returns.

expect excess return formula because the expected return –the expected change in the stock price scaled by the current stock price– is the sum of the expected change in the mispricing part and the expected change in the fundamental price scaled by the current stock price. Second, we can interpret CMER as the "true" alpha because it is a part of the expected excess return, which cannot be explained by the covariance risk premium term, where the covariance risk-premium term is calculated as the covariance between the asset return and the *true* IMRS; we use no specific model to proxy IMRS and hence alpha is not affected by any mis-specification bias. Therefore, CMER does not represent a risk premium. Rather, it reflects the out-/under-performance due to the existence of market frictions. In the next subsection, we discuss another interpretation of CMER once we reveal the relation between CMER and option prices. Finally, equation (11)) echoes the model of Gârleanu and Pedersen (2011). In their model, a similar asset pricing equation appears where a mispricing term appears on top of the covariance risk premium term. Our model differs though in that we make no assumption about the source of frictions nor the functional form of IMRS.

2.3 Estimation of CMER using market option prices

Equation (12) shows that CMER is a function of the mispricing variable M and the IMRS. Since these variables are not observable, equation (12) cannot be used to estimate CMER; it serves only to define and interpret CMER. We develop a formula which allows to calculate CMER by using equity options' market prices as inputs. To this end, we assume that the option market is frictionless. In Appendix C, we relax this assumption; we repeat the subsequent empirical analysis and we find that results are qualitatively similar to the ones obtained under frictionless option markets. We also assume that the dividend payment in the next period 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, say, one-month, because the near future dividend payments are usually pre-announced. Under this setting, we obtain the following result.

Theorem 2.2 *For any strike K, the following equation holds:*

$$CMER_{t,t+1} = \frac{R^0_{t,t+1}}{S_t}(C_t(K) - \widetilde{C}_t(K)), \quad where \tag{13}$$

$$\widetilde{C}_t(K) = P_t(K) + S_t - \frac{K + D_{t+1}}{R^0_{t,t+1}}, \tag{14}$$

Proof: See Appendix A.2.[6] □

Theorem 2.2 provides the formula to estimate CMER because the right hand side of (13) is observable as long as a pair of European call and put options with the same maturity and strike is available. In Section 3.2, we explain how we compute CMER.

We can interpret $\widetilde{C}_t(K)$ as a hypothetical call option price converted from the put option price via the standard put-call parity in the case where put-call parity would hold; due to market constraints, this may not be the case (i.e., $\widetilde{C}_t \neq C_t$ in general). Therefore, equation (13) provides another interpretation of CMER; CMER is proportional to the degree of the violation of the put-call parity, $C_t(K) - \widetilde{C}_t(K)$ scaled by the ratio of the gross risk-free return to the current stock price. In particular, CMER is zero if and only if the put-call parity holds. Positive (negative) CMER is equivalent to $C_t(K) > \widetilde{C}_t(K)$ ($C_t(K) < \widetilde{C}_t(K)$), meaning that the call is relatively more expensive (cheaper) than the put given the put-call parity.

Two remarks are in order. First, we explain why option prices may convey information about the underlying stock mispricing. Intuitively, we expect that the estimated CMER will convey information about stock mispricing because the violation of put-call parity stems from mispricing in the underlying stock and/or in the option market. Given that equations (13) and (14) are derived assuming frictionless option markets, a non-zero CMER is a result of mispricing only in the stock market. In Appendix C, we find that CMER is still related to stock mispricing even when we relax the assumption of frictionless option markets. This suggests that mispricing in the option market is of second order importance regarding the

[6]Note that the proof of Theorem 2.2 relies on the implicit assumption that both the stock and options are priced by the same IMRS. This is in line with the empirical evidence in He et al. (2017), who find that financial intermediaries are the marginal investor in a number of markets, including the stock market and the derivatives market.

ability of the CMER-formula shown in Theorem 2.2 to capture stock mispricing. Second, as Cremers and Weinbaum (2010) show, the violation of the put-call parity is equivalent to the non-zero implied volatility spread (IVS). In line with this, in Section 5.2 we show that the right hand side of (13) can be approximated using IVS.

2.4 Testable hypotheses

Our model yields three testable hypotheses regarding the relation of CMER, expected asset returns and frictions.

Hypothesis 1: The asset's expected return is increasing with CMER.

Equation (11) shows that the greater CMER is, the greater the asset's expected returns. Therefore, we expect that when we sort stocks based on the estimated CMER in portfolios, the post-ranking portfolios' average return and CMER will be positively related.

Hypothesis 2: When the "CMER-adjusted excess return" $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$ is regressed on a set of risk-factors that represent the covariance risk premium term, the intercept should be zero.

Again, this hypothesis is implied by Equation (12). Finally, we have the following hypothesis regarding the relation between CMER and transaction costs.

Hypothesis 3: Higher transaction costs imply a wider range of CMER values.

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:*

$$-\frac{2\rho}{1+\rho} R^0_{t,t+1} \leq CMER_{t,t+1} \leq \frac{2\rho}{1-\rho} R^0_{t,t+1}. \tag{15}$$

Proof: See Appendix A.3. □

Proposition 2.1 yields the third testable implication: stocks which exhibit higher transaction costs may take more extreme CMER values. We will test this hypothesis via three alternative routes. First, we will eyeball the times series evolution of the CMER's variation and discuss it in the light of major market events. We expect that the more distressed the market is, the greater the CMER's variation. Second, we will examine the relation of CMER with firm and stock characteristics; this will be done by sorting stocks in portfolios according to their CMER values. We expect that the portfolios which are subject to greater frictions will exhibit more extreme CMER values. Third, we will investigate the performance of spread portfolios formed by a dependent bivariate sorting exercise. In particular, we will first sort stocks in portfolios by their respective transaction cost proxy. Then, within any given portfolio, we will sort stocks in portfolios based on their respective CMER and we will calculate the spread portfolios' returns. We expect that the average return of the spread portfolios will increase as a function of the transaction cost proxy. This is because the higher transaction costs are, the more extreme CMER is expected to be and hence the greater the expected return of the spread portfolios due to Hypothesis 1. We discuss these in Sections 3.3 and 4.3.

3 Data and estimation strategy

3.1 Data sources

We obtain option implied volatility data from the OptionMetrics Ivy DB database (OM) via the Wharton Research Data Services. Even though options on the U.S. individual equities are American style, OM extracts the Black and Scholes (1973) implied volatilities (BS-IV) by deducting the early exercise premium from the American option market price as this is calculated by the Cox et al. (1979) binomial tree model. We obtain the risk-free rate and dividend payment history from the OM database to calculate the present value of dividend payments over the option's life time. Our dataset spans January 1996 to April 2016 (244 months). We retain option data on each end of month trading day. Then, we remove BS-IVs if the recorded bid price is non-positive, the IV is missing, and the 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.

Stock returns are obtained 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 online data library. We obtain the factors in Stambaugh and Yuan (2017) 4-factor mispricing factor model from Yu Yuan's website. In addition, we construct various stock characteristics variables (e.g., size, book-to-market, bid-ask spread) based on the CRSP and the Compustat database. For the definition and the data source of the various stock characteristics variables, see Appendix B.

3.2 Computation of CMER: Choice of strikes and maturities

Theorem 2.2 shows that we can estimate CMER from the market prices of *European* call and put equity options with the same maturity and strike. However, we cannot apply this formula to the U.S. individual equity options data because these are American options. We circumvent this obstacle by backing $C_t(K)$ and $\widetilde{C}_t(K)$ from the call and put BS-IV, $IV_t^c(K)$ and $IV_t^p(K)$, provided by OM. These are extracted from American options whose prices have been adjusted for the early exercise premium; the Black-Scholes option pricing formula for the case where the underlying asset pays discrete dividends is used to establish the mapping from BS-IVs to $C_t(K)$ and $\widetilde{C}_t(K)$.

CMER depends on the strike and maturity of the option employed to calculate the right hand side of equation (13). We deal with the choice of these two parameters as follows. Regarding the choice of strike, on each end-of-month date t and for each traded option maturity T, we calculate the right hand side of equation (13) for each strike K, at which both $IV_t^c(K)$ and $IV_t^p(K)$ are available and denote it as $CMER_{t,T}(K)$. Then, we take the weighted average of them across strikes:

$$CMER^{AVE}_{t,T} = \sum_{K \in \mathcal{K}} \omega(K)\, CMER_{t,T}(K), \tag{16}$$

where $\mathcal{K}$ is a set of strike prices with valid IV^c_t and IV^p_t 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 $\omega(K)$ (see e.g., Cremers and Weinbaum (2010)). This weighted average procedure is in line with the previous literature to reduce possible measurement error issues in the empirical options data. As a robustness check, we also compute the forward-at-the-money (ATM) $CMER^{ATM}_{t,T}$ for a given maturity T, defined as

$$CMER^{ATM}_{t,T} = CMER_{t,T}(K^*), \tag{17}$$

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 over the period $[t+1, T]$.

Regarding the choice of the options' maturity to be used for the calculation of CMER, 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 CMER and we will examine certain properties of the post-ranking monthly returns. Therefore, the horizon of the estimated CMER should correspond to the horizon of expected excess returns. To this end, first we multiply each estimated CMER by $30/DTM$, where DTM denotes days-to-maturity. Then, we construct the 30-day constant maturity CMER (CM CMER) by linearly interpolating the two traded maturities surrounding the 30-day maturity. The estimated CMER 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 CMER from the closest to 30-days to-maturity options (CLS CMER) as an alternative to the 30-day constant maturity CMER. It is expected that the CMER computed under this approach becomes noisier 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 CMER as missing.

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

3.3 CMER: Summary statistics

Table 1, Panel A, reports the summary statistics of the estimated CMER on the end of each month for the four ways of estimating CMER. We can see that there is about 333,000 stock-month CMER observations for the case of the AVE-CM and ATM-CM CMER, whereas this number increases to about 347,000 observations for the case of the AVE-CLS and ATM-CLS CMER. Since there are 244 months in our data period, there are one average about 1,370 (1,420) stocks in each month in the case of AVE-/ATM-CM CMER (AVE-/ATM-CLS CMER) case; this is a sufficient number to form well diversified decile portfolios in the subsequent analysis. The mean and the median of the estimated CMER are about -0.1% and -0.04% per month (30-day), respectively. Results are similar across the four construction methods of CMER. The distribution of CMER is skewed to the left and it is highly leptkurtic. The estimated CMER is sizeable; 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 CMER. It 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 depending on the CMER construction method. This magnitude of variation is relatively large compared to the long-run average U.S. equity risk premium, which is about 6% per year, or 50 bps per month (see e.g., Mehra (2012)). The percentage of the positive observations of CMER is about 45% in any of the four construction methods of CMER, which means that CMER takes negative values more often that positive values. Table 1, Panel B, reports that the four ways of computing

CMER are almost perfectly correlated. Therefore, the subsequent analysis is expected to be robust to the choice of the method to estimate 30-day CMER.

[Table 1 about here.]

Figure 1 shows the monthly time-series of the median CMER. The median time-series have typically been taking negative values until the recent financial crisis. Since the median CMER is negative, it means that there are more stocks with negative CMER than positive CMER (the proportion of positive CMER had been around 38% until 2006). This observation is consistent with Ofek et al. (2004) who study the violation of the put-call parity. They examine the sign of $C_t(K) - \widetilde{C}_t(K)$, which is the same as that of $CMER_{t,t+1}$.[7] By using data from July 1999 to November 2001, Ofek et al. (2004) show that $C_t(K) - \widetilde{C}_t(K)$ is positive for one third of their sample, very close to our result of 37% during the same period. However, after the financial crisis, the median of the estimated CMER starts to take both positive and negative values and its variability has increased.

[Figure 1 about here.]

Figure 2 shows the interquartile range (IQR) of AVE-CM CMER. We prefer this statistic to measure the dispersion of the estimated CMER to the standard deviation because the distribution of CMER is highly skewed and leptokurtic. As we have discussed in Section 2.4, the degree of the dispersion in CMER is determined by the size of transaction costs and hence by the degree of market frictions (Hypothesis 2). The time-series fluctuations in the IQR are in line with the theoretical predictions: most of the spikes in the IQR corresponds to market turmoils, such as Russian default and LTCM crisis (August–September 1998), the collapse of Lehman Brothers and ensuing market meltdown (September–November 2008), European debt crisis (November 2011, uncertainty was the highest around the general election in Greece), and

[7] Precisely speaking, Ofek et al. (2004) calculate the put-call parity implied stock price $S_t^* := C_t(K) - P_t(K) + K/R^0_{t,t+1}$ for non-dividend paying stocks and investigate the signs of the ratio $\log(S_t/S_t^*)$ and its predictive power for future returns. From the definition of $\widetilde{C}_t$ (equation (14)), it follows that $C_t(K) - \widetilde{C}_t(K)$ and $\log(S_t/S_t^*)$ have the same sign, that is, Ofek et al. (2004) effectively study the sign of $CMER_{t,t+1}$.

the Chinese stock market turmoil (June 2015–January 2016).[8]

[Figure 2 about here.]

4 Testable predictions: Empirical evidence

In this section, we examine the testable predictions (Hypotheses 1,2, and 3) of our CMER asset pricing model discussed in Section 2.4.

4.1 Predictive power of CMER for future returns

First, we test Hypothesis 1 that CMER predicts future stock returns; stocks with higher CMER should earn a higher expected return compared to stocks with a lower CMER. To this end, we examine whether CMER predicts equity returns cross-sectionally by taking a portfolio construction approach. We sort stocks in decile portfolios by using the estimated CMER as a sorting criterion. Portfolio 1 contains the stocks with the lowest CMER and Portfolio 10 the stocks with the greatest CMER. We form portfolios at the end-of-each month. Then, we calculate the post-ranking returns of each portfolio and the return of the zero-cost long-short spread portfolio, where we go long in the portfolio with the highest CMER stocks and short in the portfolio with the lowest CMER stocks. 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 CMER 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 CMER. Moreover, the average return of the long-short value-weighted spread portfolio is 1.64% per month (20% per year). This value is economically significant and also statistically significant (t-stat; 5.77). We also calculate the risk-adjusted returns, in

[8] 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 microstructure friction measure takes greater values during recessions and market distress periods.

terms of alpha with respect to the CAPM and Carhart (1997) four-factor (FFC) model.[9] Both CAPM- and FFC-alpha are economically and statistically significant; α_{CAPM} is 1.70% and α_{FFC} is 1.86% per month and their t-statistics are above five. These results shows that the estimated CMER predicts future stock returns.

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 (21% per year) and 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.[10] Moreover, as the value-weighted construction tends to result in lower alphas and t-statistics, our judgment on the existence of the CMER term will be more conservative and hence more credible.

[Table 2 about here.]

Next, we examine whether this performance stems from the first day of the post-ranking period or from a longer period, i.e. we examine whether the predictive ability of CMER is short-lived. First, we investigate to what extent the performance is attributed to the first trading day. We estimate the return of the AVE-CM CMER-sorted deciles portfolios by skipping the first trading day after the portfolio formation day and compare the result to the benchmark result, where stocks are traded immediately after the portfolio formation.[11] Table 3 shows

[9]For all portfolio sort exercises in this Section, we also estimate alphas with respect to the Fama and French (1993) three-factor model, Fama and French (2015) five-factor model, and Stambaugh and Yuan (2017) mispricing-factor model. Results are qualitatively similar and hence we do not report them due to space limitations.

[10]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).

[11]To obtain the monthly returns, where the first trading day is skipped, we divide the gross monthly return provided by the CRSP monthly stock file by the gross daily return on the first trading-day, which we obtain from the CRSP daily stock file.

that the average return of the spread portfolio decreases 102 bps (from 164 to 62 bps) and α_{FFC} decreases 100 basis points once we skip the first trading day after the portfolio formation date. Albeit the average return and α_{FFC} decreases significantly compared to the ones obtained from the full post-ranking period, they are still significant. This result implies that about 60% (50%) of the average monthly return (the risk-adjusted return) is attributed to the first day of the post-ranking month, yet CMER retains its predictive power beyond the first day of the post-ranking period.

[Table 3 about here.]

Next, we examine further how the predictive power of CMER decays over the post-ranking period. Table 3, Panel B, reports the results in the case where we repeat the above empirical analysis by skipping the first five trading days. We can see that the average return and α_{FFC} decreases to 51 bps (65 bps) when we skip the first trading week (five trading days), yet the average return (α_{FFC}) is still significant at a 5% (1%) significance level. Table 3, Panel C, reports the results when we skip the first seven trading days. We can see that in this case both the average return and α_{FFC} become insignificant. These results suggest that the predictive power of CMER disappears seven trading days after the portfolio formation date.

4.2 Alpha of the CMER-adjusted excess returns

Next, we examine Hypothesis 2 that the intercept of the regression of the "CMER-adjusted excess returns:" $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$ on a set of risk factors that describes the market-maker's IMRS, should not be statistically different from zero. To test this hypothesis, we need to specify an asset pricing model, i.e., a set of specific risk factors. Note that this gives rise to a joint hypothesis problem. In the case where the intercept is statistically different from zero, it can be the case that our hypothesis does not hold, but also it can be the case that the set of risk factors does not describe the IMRS well. To overcome this difficulty, we estimate the intercepts for five asset pricing models, 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. If the intercept is zero regardless of the choice of widely accepted asset pricing models, this would reinforce the validity of Hypothesis 2.

Table 4, Panel A, reports the intercepts of regressions, where we regress the CMER-adjusted excess returns, $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$, of the value-weighted decile portfolios and the spread portfolio. We can see that all intercepts are statistically insignificant at a 5% significance level. This suggests that the estimated CMER represents the true alpha of the decile portfolios. On the other hand, the intercepts of the spread portfolios are still statistically significantly different from zero when we use the CAPM as the benchmark asset pricing model. These results may be driven by outliers of the estimated CMER (which are in the two extreme portfolios by the definition of outliers). To examine this possibility, we repeat our analysis by discarding CMER values below 1st percentile point or above 99th percentile point of the CMER distribution across all stocks. Then, we sort stocks by the estimated CMER. Table 4, 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 truncation of outlier CMER). 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 intercept is not statistically different from zero in all cases. In sum, the intercepts of the spread portfolio are insignificant, irrespective of the choice of the asset pricing model.[12] Overall, these results validate our second hypothesis.

[Table 4 about here.]

4.3 Characteristics of CMER-sorted portfolios

Next, we provide two alternative ways to test Hypothesis 3 as discussed in Section 2.4. First, we examine the relation between the estimated CMER and various firm and stock characteristics. Table 5 reports these characteristics for the CMER-sorted value-weighted decile portfolios,

[12]Note that this does not imply that all considered models price the cross-section of U.S. equities equally well and hence it does not contradict previous studies which document that the pricing performance of these models differs. Our results show that all models price the *particular* cross-section of the CMER-sorted decile portfolios and their spread portfolio equally well.

where we use the AVE-CM CMER as a sorting variable. Hypothesis 3 suggests that stocks with higher transaction costs are likely to exhibit more extreme CMER 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 CMER, that is, stocks with extreme estimated CMER values tend to have a wider bid-ask spread, greater illiquidity and lower stock prices. There is an inverse U-shaped relation between CMER 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 CMER and the idiosyncratic volatility (IVOL) and the beta; stocks with extreme CMER value tend to have larger idiosyncratic risk and systemic risk. These relations are again consistent with Hypothesis 3 because a higher riskiness can be interpreted as a larger 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 CMER and variables which measure short-selling costs, i.e., the relative short interest (RSI) (see Asquith et al. (2005)), and the estimated shorting fee (ESF) of Boehme et al. (2006). This is again consistent with Hypothesis 3 because short-selling costs are part of transaction costs. Finally, we also find a U-shaped relation between the book-to-market ratio (B/M) and the estimated CMER.

[Table 5 about here.]

Second, we examine Hypothesis 3 by analysis based on dependent bivariate sort as discussed in Section 2.4; the variation of CMER will be greater within a group of stocks that is subject to larger transaction costs and market frictions. The CMER-spread portfolio formed from stocks with larger CMER variation is expected to earn a higher average return because larger CMER variation means that the expected relative out-performance (under-performance) 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 CMER, the CMER-spread portfolios' average returns will be higher for a higher transaction costs' bin. To confirm this conjecture, we conduct bivariate dependent sorts first by a friction-related variable, then by the estimated CMER. Table 6, Panel A, reports the bivariate dependent sort, first by the bid-ask spread, then by CMER. The result verifies our conjecture. The average CMER of the CMER-sorted spread portfolio increases with the level of the relative bid-ask spread. The average return and α_{FFC} of the CMER-sorted spread portfolios also increase with the level of the bid-ask spread. We find a similar pattern in the CMER-sorted portfolios in Table 6, Panel B, where we use the SIZE as an alternative sorting proxy for transaction costs. In general, the average CMER, average return, and α_{FFC} of the CMER-sorted spread portfolios decrease in the level of SIZE.[13]

[Table 6 about here.]

4.4 Robustness checks

In this subsection, we report a number of robustness checks. First, we examine whether our baseline results may differ across the four possible ways of constructing CMER. We also investigate whether results are driven by outliers, stock reversals, non-synchronous trading in the option and underlying market. We also conduct Fama and MacBeth (1973) regression tests to see whether CMER is related to stock returns.

First, we examine whether the average return and α_{FFC} of the decile spread portfolio differ across the four CMER proxies. Table 7, Panel A, reports the results. We can see that the average return and α_{FFC} are statistically and economically significant for any of the four ways of computing CMER in both the value-weighted and equally-weighted cases. In addition, we can see that CMER computed by the AVE-CM method delivers the highest average return and alpha. This may be due to the fact that AVE-CM CMER reduces any measurement errors in CMER 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 30-day constant maturity CMER gives cleaner signals for future out-/under-performance in the succeeding month than CMER at the traded maturity closest to 30-day.

[13] 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.

[Table 7 about here.]

Second, regarding the effect of extreme CMER values, we check whether the predictive power of CMER is driven by few stocks that have extreme CMER value. We perform two alternative robustness tests based on two respective ways of forming portfolios. First, we remove stocks whose CMER is below 1st percentile point or above 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 reports the average return and the risk-adjusted return of the decile spread portfolio, where we remove stocks whose CMER is below 1st percentile point or above 99th percentile point. Two spread portfolios are formed 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 CMER 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 8 show the analogous results for the CMER-sorted quintile portfolios. Again, the average and risk-adjusted returns are economically and statistically significant.

Third, the predictability of CMER 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 CMER. Hence, we can see whether CMER has predictive power after the previous month return is controlled. The first five columns of Table 8 reports the average returns of the 25 bivariate-sorted portfolios. The sixth to last columns report the average return, α_{FFC}, and the average CMER of the long-short portfolios of CMER, after controlling the previous month return. 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 CMER 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 CMER 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 CMER 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 the investor cannot exploit the CMER signal since the stock market has closed and hence he cannot trade stocks.[14] In this case, inevitably, the investor will trade stocks at the open of the next day. To examine whether the calculated at the end-of-day CMER 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 day that follows the estimation of CMER.

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%. α_{FFC} 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 CMER prevails even in the presence of non-synchronous trading in the stock and option market; the predictive power of CMER does not change overnight. On the other hand, given that the predictive performance of CMER deteriorates (yet it remains significant) once we skip the first trading days, the predictive power of CMER starts to decay from the intra-day trading on the first trading date after the CMER observation date.

[Table 9 about here.]

[14]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. (EST). However, on June 23, 1997, CBOE changed the closing time for options on individual stocks to 4:02 p.m. (EST), i.e. only two minutes after the closing of the underlying stock market. This change minimizes the potential non-synchronicity bias during our sample period. Nevertheless, in the absence of intra-day option prices, it is not known whether the CMER estimates were available in real time before the stock market close.

Fifth, we examine whether results are robust in the case where we exclude stocks with small prices. Table 9, Panel B, reports the portfolio analysis 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.[15] 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 mispricing-related variables, where the predictability mainly stems from small, low priced stocks which are more susceptible to mispricing.[16]

Sixth, we examine whether the predictive cross-sectional power of CMER prevails in the case where we use different breakpoints to form the decile portfoliosTable 9, Panel C, reports the portfolio sort result, where we form decile portfolios based on the NYSE breakpoints.[17] 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 CMER 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.

Seventh, we examine whether the predictive power of CMER still exists over two sub-periods. We divide our initial sample period into January 1996– December 2006 and January 2007–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 CMER values as Figures 1

[15]Typically, the threshold price level is set to \$1 or \$5. We adopt a greater threshold price level because there is a negligible number of stocks whose price level is below \$5; these stocks do not have a liquid option market and thus they had been already excluded from our CMER sample by the option filtering criteria.

[16]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.

[17]To form CMER-sorted decile portfolios, we need to determine nine breakpoints, $b_1 < b_2 < \cdots < b_9$ such that a stock with CMER value $CMER^i$ belongs to j-th portfolio when $b_{j-1} < CMER^i \leq b_j$. In the baseline analysis, b_j are calculated as 10th, …, 90th percentile of the CMER of *all* stocks. In the NYSE breakpoint method, these percentiles are calculated using *only* NYSE stocks, and then we form decile portfolios using *both* NYSE and non-NYSE stocks.

and 2 have indicated. Second, December 2006 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.[18] 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.

[Table 10 about here.]

Finally, we complement the portfolio sorts with Fama and MacBeth (1973) (FM) regressions where we regress stock returns on stock's characteristics including the estimated CMER. 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)). For each month t ($t = 1, 2, ..., T$), we estimate the following cross-sectional regression across individual stocks indicated by i ($i = 1, 2, ..., n$):

$$R_{t,t+1} = \alpha + \beta' X_{i,t}, \tag{18}$$

where $X_{i,t}$ is a vector that contains characteristics variables of individual stocks. Then, we calculate the time-series average and the HAC-adjusted 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 variables in $X_{i,t}$ at a 1% threshold level.

Table 11 reports the result. Model (1) shows that the estimated CMER is highly positively related to the stock returns. In Model (2), we include 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 $R_{t-1,t}$, idiosyncratic volatility (IVOL), asset growth rate and profitability since

[18] 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.

it is well-known that these variables have predictive power for future stock returns (see e.g., 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 CMER is still positive and highly statistically significant even after controlling for these variables. 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 CMER is virtually unchanged from Model (2).

In columns (4) to (9), we report results from conducting analysis on two separate subsamples. 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 CMER are still highly significant regardless of whether we use only NYSE/AMEX stocks or NASDAQ stocks. Next, as we have seen in Table 5, CMER 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 CMER; we split our sample into two parts where the splitting points is a zero CMER 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 CMER 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 CMER is larger for negative CMER samples, but the coefficient of CMER is significant for both subsamples. Finally, we split our sample into January 1996–December 2006 and January 2007–April 2016 as before and we re-apply the FM regressions. We can see from the last two columns that the estimated coefficient on CMER becomes slightly smaller in the latter period, but they are highly statistically significant in both sub-periods.

[Table 11 about here.]

5 Relation to option-implied measures of mispricing

In this section, we discuss the relation of CMER with three option-implied measures of mispricing, which have been documented to predict stock returns cross-sectionally by the previous literature: the option-implied stock price of Manaster and Rendleman (1982), the implied volatility spread (IVS) (e.g., Bali and Hovakimian (2009) and Cremers and Weinbaum (2010)), and DOTS measure. Moreover, we discuss how CMER relates to the mispricing term suggested by Brennan and Wang's (2010) (BW) mispricing risk premium (MPR) and Hou et al.'s (2016) (HKW) FRIC measure.

5.1 Manaster and Rendleman's (1982) measure

Manaster and Rendleman (1982) define the implied stock price S_t^* as the parameter that minimizes the sum of squared errors between observed option prices and the "theoretical" option prices given by the Black and Scholes (1973) model. They assume that S_t^* proxies the current fundamental price and hence they propose the following proportional error of the stock Δ_t as a proxy of the current mispricing:

$$\Delta_t = \frac{S_t^* - S_t}{S_t}. \tag{19}$$

Using the relation between IMRS and the $\mathbb{Q}$-probability measure (Aït-Sahalia and Lo (1998)), we have

$$\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* X_{t+1}] = \frac{1}{R_{t,t+1}^0}\mathbb{E}_t^{\mathbb{Q}}[X_{t+1}], \tag{20}$$

where X_{t+1} is any payoff at time $t+1$. The following Proposition shows the relation between Δ_t and CMER:

Proposition 5.1 *When S_{t+1} follows a log-normal distribution under the $\mathbb{Q}$-measure, the following relation holds:*

$$\Delta_t = \frac{1}{R_{t,t+1}^0} CMER_t. \tag{21}$$

Proof: See Appendix A.4. □

Two remarks on Proposition 5.1 are in order. First, this Proposition shows that Δ_t does not measure the current mispricing. Rather, Δ_t is the discounted value of CMER, which is the expected change in mispricing. Second, Δ_t measures the discounted CMER only if the risk-neutral distribution of the asset return is normal. The empirical evidence shows that the risk-neutral distribution of returns is not normal (e.g., Kostakis et al. (2011) and references therein). In such a case Δ_t will be a biased estimate of CMER; Manaster and Rendleman (1982) also document a weak cross-sectional predictive performance of Δ_t.[19]

5.2 Relation to IVS and DOTS

Previous literature has documented that IVS, defined as the difference between the BS-IV of the call and put options with the same strike and maturity, predicts future stock returns (see e.g., Bali and Hovakimian (2009), Cremers and Weinbaum (2010)). In addition, Goncalves-Pinto et al. (2017) find that their proposed option-implied measure, DOTS, also predicts the cross-section of future stock returns and that DOTS is highly correlated with IVS. In this subsection, we show that both IVS and DOTS are approximately proportional to CMER. We begin by providing the following Proposition which establishes the relation between CMER and IVS.

Proposition 5.2 *Let $IV_t^c(K)$ and $IV_t^p(K)$ be the Black-Scholes call and put implied volatilities (BS-IVs), respectively. Then, the following approximate equation holds.*

$$CMER_t(K) \approx \frac{R^0_{t,t+1}\mathcal{V}_t(K)}{S_t}(IV_t^c(K) - IV_t^p(K)), \tag{22}$$

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

Proof: See Appendix A.5. □

Next, we show the relation between CMER and Goncalves-Pinto et al.'s (2017) DOTS

[19] We estimate Manaster and Rendleman's (1982) S_t^* by minimizing the squared sum of the difference between European option prices converted from the OM BS-IVs and Black and Scholes (1973) theoretical prices, and then we calculate Δ_t. We do not find a significant average and risk-adjusted returns of Δ_t-sorted decile spread portfolio. This implies that the Manaster and Rendleman's (1982) measure does not predict stock returns cross-sectionally, as expected.

measure. DOTS is calculated from a pair of American call and put option prices as

$$DOTS_t(K) := \frac{\frac{S_t^U(K)+S_t^L(K)}{2} - S_t}{S_t}, \tag{23}$$

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. Goncalves-Pinto et al. (2017) assume that the mid-price of the American option-implied bounds S_t^U and S_t^L proxies the true value of the stock price.

Proposition 5.3 *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:*

$$DOTS_t(K) = \frac{CMER_{t,t+1}(K)}{R_{t,t+1}^0} + u_t, \quad u_t = \frac{1}{S_t}\left[\eta_t^c - \frac{D_{t+1}}{2R_{t,t+1}^0} - \left(\eta_t^p - \frac{K(R_{t,t+1}^0 - 1)}{2R_{t,t+1}^0}\right)\right]. \tag{24}$$

Proof: See Appendix A.6. □

Proposition 5.3 shows that DOTS is the discounted observable part of CMER plus an additional term u_t which is a function of the early exercise premium of the American call and put options. The extent to which CMER will be highly correlated with DOTS will depend on the size of u_t.

Propositions 5.2 and 5.3 explain theoretically the empirically documented predictive power of IVS and DOTS for future stock returns; they are approximately proportional to CMER, which is a part of expected stock returns when mispricing exists. 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 CMER, IVS and DOTS as a cross-sectional predictor of stock returns may differ since IVS and DOTS are proxies of CMER; the strength of the predictive power will depend on the size of approximation errors in equation (22) in the case of IVS and on the size of u_t in the case of DOTS. The predictive power of IVS 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.

We compare the cross-sectional predictive ability of AVE-CM CMER 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 CMER, IVS and DOTS. We can see that the CMER-sorted spread portfolio earns greater alphas by 45–49 bps (27–42 bps) compared to the IVS-sorted (DOTS-sorted) portfolio. The difference between CMER and DOTS alphas is smaller than that between CMER 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.[20] In sum, in line with the previous literature and Propositions 5.2 and 5.3, both IVS and DOTS predict stock returns, yet CMER outperforms them. This is expected since CMER is part of the expected stock return as our formal asset pricing model shows whereas the other two measures are approximations of CMER.

[Table 12 about here.]

5.3 Relation to BW and HKW's mispricing model

Brennan and Wang (2010) (BW hereafter) and Hou et al. (2016) (HKW) propose asset pricing models, where they employ a reduced form mispricing model to study how the existence of mispricing affects asset returns. The two studies show that the existence of mispricing results in what they call the *mispricing risk premium* (MRP) and the FRIC measure, respectively. First, we shortly overview their main theoretical results. BW and HKW's model have a similar structure. Specifically, they define mispricing by the following equation.

$$S_t = F_t Z_t \quad \text{in BW} \quad \textit{and} \quad S_t = F_t(1+\varphi_t) \quad \text{in HKW,} \tag{25}$$

[20]We calculate u_t as $DOTS_t(K) - CMER_{t,t+1}(K)/R^0_{t,t+1}$ 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.

where S_t and F_t are the market price and the fundamental price of the stock, respectively. In short, in these two models, the stock price is described as $S_t = F_t \mu_t$ with $\mu_t = Z_t$ in BW and $\mu_t = 1 + \varphi_t$ in HKW. We call μ_t as the *mispricing multiple.* BW and HKW assume the following time-series structure for the mispricing multiple μ_t.

$$\text{(BW:)} \quad z_t = \rho z_{t-1} + \varepsilon_t \quad \text{where } \varepsilon_t \text{ is an } i.i.d. \text{ normal term and } z_t = \log Z_t = \log \mu_t, \tag{26}$$

$$\text{(HKW:)} \quad \varphi_t \text{ follows a zero-mean } i.i.d. \text{ process, where } 1 + \varphi_t = \mu_t. \tag{27}$$

In addition, both BW and HKW assume that the fundamental price and the mispricing multiple are independent. In analogy to this assumption, we assume that IMRS $m^*_{t,t+1}$ is independent of the future mispricing M_{t+1}. To simplify the subsequent discussions, we also assume that the stock pays no dividends.[21] Under these assumptions, we obtain the following result.

Proposition 5.4 *Let $R^F_{t,t+1} = F_{t+1}/F_t$ be the fundamental return. Then, the following equation holds:*

$$\mathbb{E}^{\mathbb{P}}[R_{t,t+1}] = B + \mathbb{E}^{\mathbb{P}}[R^F_{t,t+1}], \tag{28}$$

where B captures the effect of stock mispricing to the expected return and it is given by

$$B \approx \begin{cases} B_{BW} = (1-\rho)\sigma_z^2 > 0 & \textit{under the specification } (26), \\ B_{HKW} = \sigma_\varphi^2 > 0 & \textit{under the specification } (27), \end{cases} \tag{29}$$

where σ_z^2 is the unconditional variance of the log mispricing process z_t in equation (26) and σ_φ^2 is the unconditional variance of φ_t in equation (27).[22] *BW call B_{BW} the mispricing risk premium (MRP) and HKW calls B_{HKW} the FRIC measure.*

Furthermore, B in equation (28) satisfies the following approximate relation:

$$B \approx \mathbb{E}^{\mathbb{P}}[CMER_{t,t+1}]. \tag{30}$$

[21]This assumption does not alter the conclusion on BW and HWK because BW report that the effect from dividend payments to their mispricing term is negligible and HKW assume that stocks pays no dividends.

[22]Equation (28) is a modified version of BW's (HKW's) original equation (6) (equation 8). Note that in BW paper, B is decomposed into four components B_i ($i = 1, 2, 3, 4$).

Proof: See Appendix A.7 □

Proposition 5.4 shows that the unconditional mean of CMER is approximately equal to MRP or FRIC measure in the BW and HWK setting, respectively, which are shown to be positive in equation (29). This means that the unconditional average of CMER should be positive under the BW or HWK's assumptions. The positivity of B_i is a consequence of the time-series specifications of the mispricing multiple μ_t in equations (26) and (27) as well as the assumption that the mispricing multiple and the fundamental price are independent. On the other hand, the mean of our model-free estimated CMER is negative (Table 1). This discrepancy implies that the BW/HWK assumptions are not supported by the data.

6 Conclusion

We examine the contribution of mispricing to expected returns (CMER) within a general asset pricing setting. To this end, we employ a financial intermediary-based equilibrium asset pricing model in the presence of stock mispricing due to market frictions. The model contains CMER, on top of the typical covariance risk-premium term calculated as the covariance between the market-maker's intertemporal marginal rate of substitution (IMRS) and the stock return. CMER reflects the expected change in mispricing over a time period. It does not reflect compensation for risk, rather it is the alpha of the stock, i.e., it reflects whether the stock outperforms/under-performs. Moreover, it is the *true* alpha in the sense that it is a part of expected excess returns that cannot be explained by the covariance risk premium term, where the covariance is taken between the agent's model-free IMRS and the stock return. We derive a model-free option-based formula to estimate CMER. The formula relates CMER to the degree of the violation of put-call parity due to stock mispricing. In contrast to the previous literature, we make no assumptions on the source and dynamics of mispricing as well as on the form of IMRS in order to derive our model and CMER formula.

We estimate CMER for a large cross-section of U.S. common stocks and we confirm the testable predictions of our model. Four are our main findings. First, CMER is sizable. This implies that expected changes in mispricing are part of expected returns. Second, we find that CMER predicts future stock returns cross-sectionally. Third, we find that the regressions of the CMER-adjusted excess return $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$ of CMER-sorted decile portfolios on a set of standard risk-factors yield non-significant intercepts. Fourth, we document that the cross-section of CMER becomes more dispersed when transaction costs and market frictions are larger.

Finally, we use our asset pricing model and show the theoretical relation between CMER and other option-implied measures of stock mispricing including Manaster and Rendleman's (1982) option-implied measure, the implied volatility spread, and Goncalves-Pinto et al.'s (2017) DOTS measure. These relations provide a theoretical explanation to the previously empirically documented predictive ability of these option-implied measures for future stock returns.

A Proofs for Section 2 and Section 5

A.1 Proof of Theorem 2.1

First, we prove the following lemma.

Lemma A.1 *Let $R^F_{t,t+1} = (F_{t+1} + D_{t+1})/F_t$ be the fundamental return of the stock. The fundamental return $R^F_{t,t+1}$ satisfies the following equation:*

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

(Proof of Lemma A.1)

From equation (9), IMRS satisfies $m^*_{t,j} = m^*_{t,t+1} m^*_{t+1,j}$ for any $j > t+1$. Application of the law of iterated conditional expectations yields

$$F_t = \sum_{j=t+1}^{T} \mathbb{E}^{\mathbb{P}}_t[m^*_{t,j} D_j] = \mathbb{E}^{\mathbb{P}}_t\left[m^*_{t,t+1}\left(D_{t+1} + \sum_{j=t+2}^{T} m^*_{t+1,j} D_j\right)\right] = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(D_{t+1} + F_{t+1})]. \tag{A.2}$$

We divide both sides of equation (A.2) by F_t and use the definition of the fundamental return to obtain equation (A.1). □

Now, we prove Theorem 2.1. By applying the covariance formula $Cov_t(X, Y) = \mathbb{E}_t[XY] - \mathbb{E}_t[X]\mathbb{E}_t[Y]$ to $Cov^{\mathbb{P}}_t(m^*_{t,t+1}, R_{t,t+1})$, we obtain the following identity:

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

The definition of the stock return $R_{t,t+1}$ and the fundamental return $R^F_{t,t+1}$ yields

$$R_{t,t+1} = \frac{F_t}{S_t}\frac{F_{t+1} + D_{t+1}}{F_t} + \frac{M_{t+1}}{S_t} = \left(1 - \frac{M_t}{S_t}\right) R^F_{t,t+1} + \frac{M_{t+1}}{S_t} = R^F_{t,t+1} + \frac{M_{t+1} - R^F_{t,t+1} M_t}{S_t}. \tag{A.4}$$

The second term in the right hand side of equation (A.3) can be transformed as follows by using equation (A.4) and Lemma A.1,

$$
\begin{aligned}
R^0_{t,t+1}\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R_{t,t+1}] &= R^0_{t,t+1}\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R^F_{t,t+1}] + \frac{R^0_{t,t+1}}{S_t}\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(M_{t+1} - R^F_{t,t+1}M_t)] \\
&= R^0_{t,t+1} + \frac{R^0_{t,t+1}}{S_t}\left(\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}M_s - M_t]\right) = R^0_{t,t+1} + CMER_t.
\end{aligned} \tag{A.5}
$$

Substitution of (A.5) into (A.3) completes the proof of equation (11). □

A.2 Proof of Theorem 2.2

Under the assumption that there are no market frictions relevant to the risk-free bond and options trading, the risk-free bond price (reciprocal of the gross risk-free rate) and option prices at time t are given by the expected payoff at time $t+1$ discounted by IMRS. In particular, it follows that $1/R^0_{t,t+1} = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}\cdot 1]$, $C_t(K) = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1}-K)^+]$ and $P_t(K) = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(K-S_{t+1})^+]$. Since $C_t(K) - P_t(K) = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1} - K)]$, we can transform $C_t(K) - \widetilde{C}_t(K)$ as follows:

$$
\begin{aligned}
C_t(K) - \widetilde{C}_t(K) &= C_t(K) - P_t(K) - S_t + \frac{K + D_{t+1}}{R^0_{t,t+1}} \\
&= \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1} - K)] - S_t + \frac{K + D_{t+1}}{R^0_{t,t+1}} \\
&= \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(S_{t+1} + D_{t+1})] - S_t = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}M_{t+1} - M_t],
\end{aligned} \tag{A.6}
$$

where we use $\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}(F_{t+1} + D_{t+1})] - F_t = 0$ (equation (A.2)) to derive the last equation. Equation (A.6) shows that $R^0_{t,t+1}(C_t(K) - \widetilde{C}_t(K))/S_t$ equals $CMER_{t,t+1}$. □

A.3 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:

$$
\frac{1-\rho}{1+\rho} \leq \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R_{t,t+1}] \leq \frac{1+\rho}{1-\rho}. \tag{A.7}
$$

The expectation term in the middle of the inequalities posed by (A.7) relates to CMER as follows:

$$\begin{aligned}\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* R_{t,t+1}] &= \frac{\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1}+D_{t+t})-S_t]}{S_t}+1 = \frac{\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* M_{t+1}-M_t]}{S_t}+1 \\ &= \frac{1}{R_{t,t+1}^0} CMER_{t,t+1}+1.\end{aligned} \tag{A.8}$$

The second equality follows from $\mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(F_{t+1}+D_{t+1})-F_t]=0$ (equation (A.2)) and the third equality follows from equation (12). Substituting equation (A.8) to (A.7) and rearranging terms yields

$$-\frac{2\rho}{1+\rho} R_{t,t+1}^0 \leq CMER_{t,t+1} \leq \frac{2\rho}{1-\rho} R_{t,t+1}^0. \tag{A.9}$$

□

A.4 Proof of Proposition 5.1

Let τ be the time length between t and $t+1$ measured in yearly basis. Given $r=\log(R_{t,t+1}^0)/\tau$ and $PVD_{t,t+1}=D_{t+1}/R_{t,t+1}^0$, Manaster and Rendleman (1982) assume that $\mathbb{Q}$-distribution of S_{t+1} follows

$$S_{t+1} \sim \mathcal{LN}(\log(S_t^*-PVD_{t,t+1})+r\tau+(\sigma^*)^2\tau/2, \sigma^*\sqrt{\tau}), \tag{A.10}$$

where $\mathcal{LN}$ denotes the log-normal distribution, and the two parameters S_t^* and σ^* are obtained by fitting the theoretical option prices under equation (A.10) to observed option prices. We can calculate the $\mathbb{Q}$-expected value of S_{t+1} as follows

$$\mathbb{E}_t^{\mathbb{Q}}[S_{t+1}] = (S_t^*-PVD_{t,t+1})e^{r\tau} \Leftrightarrow S_t^* = \frac{\mathbb{E}_t^{\mathbb{Q}}[S_{t+1}+D_{t+1}]}{R_{t,t+1}^0} = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1}+D_{t+1})], \tag{A.11}$$

where we used equation (20) to obtain the last equality. Therefore, we obtain Δ_t is equal to $CMER_t/R_{t,t+1}^0$. □

A.5 Proof of Proposition 5.2

Let $BS_{call}(IV)$ be Black-Scholes call option function viewed as a function of the volatility parameter. Then, by the definition of the call BS-IV and the Black-Scholes European call option price formula, $C_t(K) = BS_{call}(IV_t^c(K))$. Let $BS_{put}(IV)$ be the Black-Scholes European put option price formula so that $P_t(K) = BS_{put}(IV_t^p(K))$. Then, it follows that

$$\widetilde{C}_t(K) = BS_{put}(IV_t^p(K)) + S_t - \frac{K + D_{t+1}}{R^0_{t,t+1}} = BS_{call}(IV_t^p(K)), \tag{A.12}$$

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 $C_t(K) - \widetilde{C}_t(K) = BS_{call}(IV_t^c(K)) - BS_{call}(IV_t^p(K))$. Therefore, a first-order Taylor series approximation of $BS_{call}(IV^c(K)) - BS_{call}(IV^c(K))$ around the mid volatility point $(IV_t^c(K) + IV_t^p(K))/2$ yields

$$C_t(K) - \widetilde{C}_t(K) = BS_{call}(IV_t^c(K)) - BS_{call}(IV_t^p(K)) \approx \mathcal{V}_t(K)(IV_t^c(K) - IV_t^p(K)), \tag{A.13}$$

where $\mathcal{V}_t(K)$ is the Black-Scholes *vega*, $\partial BS_{call}(\sigma)/\partial\sigma$, evaluated at $(IV_t^c(K) + IV_t^p(K))/2$. By substituting this approximation in equation (13), we obtain equation (22). This derivation shows that the approximation error in (22) stems from the higher-order terms of the Taylor series approximation of $BS_{call}(IV_t^c(K)) - BS_{call}(IV_t^p(K))$. □

A.6 Proof of Proposition 5.3

Substituting the definition of S_t^U and S_t^L in equation (23) yields

$$DOTS_t = \frac{1}{S_t}\left(C_t^{mid}(K) - P_t^{mid}(K) - S_t + \frac{1}{2}\left(1 + \frac{1}{R^0_{t,t+1}}\right)K + \frac{D_{t+1}}{2R^0_{t,t+1}}\right), \tag{A.14}$$

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. Furthermore, we define $\widetilde{C}_t(K) = P_t(K) + S_t - (K + D_{t+1})/R^0_{t,t+1}$ as in equation (14). Then, by rearranging the right hand side of equation (A.14) we obtain

$$DOTS_t = \frac{C_t(K) - \widetilde{C}_t(K)}{S_t} + \frac{1}{S_t}\left[\left(\eta_t^c - \frac{D_{t+1}}{2R_{t,t+1}^0}\right) - \left(\eta_t^p - \frac{1}{2}\left(1 - \frac{1}{R_{t,t+1}^0}\right)\right)\right]. \tag{A.15}$$

Since the first term in the right hand side of equation (A.15) is $CMER_{t,t+1}/R_{t,t+1}^0$, we prove equation (27). $\square$

A.7 Proof of Proposition 5.4

First, we show equations (28) and (29). Taking the ratio of equation $S_t = F_t\mu_t$ at time t and $t+1$ yields

$$\frac{S_{t+1}}{S_t} = \frac{F_{t+1}}{F_t}\frac{\mu_{t+1}}{\mu_t} \quad \Leftrightarrow \quad R_{t,t+1} = R_{t,t+1}^F\frac{\mu_{t+1}}{\mu_t}. \tag{A.16}$$

Taking the expectation of both sides of the second equation in (A.16) yields

$$\mathbb{E}^{\mathbb{P}}[R_{t,t+1}] = \mathbb{E}^{\mathbb{P}}[R_{t,t+1}^F] + B, \quad where \quad B = \mathbb{E}^{\mathbb{P}}[R_{t,t+1}^F]\mathbb{E}^{\mathbb{P}}\left[\frac{\mu_{t+1}}{\mu_t} - 1\right]. \tag{A.17}$$

Then, under the time-series specification of μ_t in equations (26) and (27), it follows that[23]

$$\mathbb{E}^{\mathbb{P}}\left[\frac{\mu_{t+1}}{\mu_t} - 1\right] \approx \begin{cases} B_{BW} = (1-\rho)\sigma_z^2 & \text{under the specification (26)} \\ B_{HKW} = \sigma_\varphi^2 & \text{under the specification (27).} \end{cases} \tag{A.18}$$

Both BW and HWK approximate $B \approx \mathbb{E}^{\mathbb{P}}[\mu_{t+1}/\mu_t - 1]$ because both $\mathbb{E}^{\mathbb{P}}[R_{t,t+1}^F - 1]$ (the net fundamental return rate) and $\mathbb{E}^{\mathbb{P}}[\mu_{t+1}/\mu_t - 1]$ (the variance of the mispricing multiple) are small and hence their product is negligible.

Now, we show equation (30). Taking the unconditional expectation of equation (A.4) yields

$$\mathbb{E}^{\mathbb{P}}[R_{t,t+1}] = \mathbb{E}^{\mathbb{P}}[R_{t,t+1}^F] + \mathbb{E}^{\mathbb{P}}\left[\frac{1}{S_t}(M_{t+1} - R_{t,t+1}^F M_t)\right]. \tag{A.19}$$

[23]For the detailed derivation of equation (A.18), see Brennan and Wang's (2010) and Hou et al.'s (2016) original articles.

Therefore, it suffices to show $\mathbb{E}^{\mathbb{P}}[(M_{t+1} - R^F_{t,t+1}M_t)/S_t] \approx \mathbb{E}^{\mathbb{P}}[CMER_{t,t+1}]$. To this end, we transform $\mathbb{E}^{\mathbb{P}}[CMER_{t,t+1}]$ as follows.

$$\begin{aligned}
\mathbb{E}^{\mathbb{P}}\left[CMER_{t,t+1}\right] &= \mathbb{E}^{\mathbb{P}}\left[\frac{R^0_{t,t+1}}{S_t}\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}M_{t+1} - M_t]\right] \\
&= \mathbb{E}^{\mathbb{P}}\left[\frac{1}{S_t}\left(\mathbb{E}^{\mathbb{P}}_t[M_{t+1}] - R^F_{t,t+1}M_t\right)\right] + \mathbb{E}^{\mathbb{P}}\left[\frac{M_t}{S_t}(R^F_{t,t+1} - R^0_{t,t+1})\right],
\end{aligned} \tag{A.20}$$

where we use the definition of CMER and the law of iterated conditional expectations to derive the first equality. The second equality follows from $\mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}M_{t+1}] = \mathbb{E}^{\mathbb{P}}_t[M_{t+1}]/R^0_{t,t+1}$, which holds under the independence assumption between m^* and M. Next, we prove that the second expectation term in the right hand side of equation (A.20) is approximately equal to zero. Due to the independence assumption between mispricing and the fundamental return, we have

$$\mathbb{E}^{\mathbb{P}}\left[\frac{M_t}{S_t}(R^F_{t,t+1} - R^0_{t,t+1})\right] = \mathbb{E}^{\mathbb{P}}\left[\left(1 - \frac{1}{\mu_t}\right)(R^F_{t,t+1} - R^0_{t,t+1})\right] = \mathbb{E}^{\mathbb{P}}\left[1 - \frac{1}{\mu_t}\right]\mathbb{E}^{\mathbb{P}}[R^F_{t,t+1} - R^0_{t,t+1}]. \tag{A.21}$$

The first expectation in the right hand side equals $\sigma_z^2/2$ under BW's assumptions and it is approximately equal to σ_φ^2 under HKW's assumptions, whereas the second term is the expectation of the excess return of the fundamental return. Note that both BW and HKW treat the product of the variance term σ_z^2 or σ_φ^2 with the expectation of the net fundamental return as being approximately equal to zero. By adopting their approximation policy, we can also treat equation (A.21) as being approximately equal to zero. This shows that $\mathbb{E}^{\mathbb{P}}\left[CMER_{t,t+1}\right] \approx \mathbb{E}^{\mathbb{P}}\left[\left(\mathbb{E}^{\mathbb{P}}_t[M_{t+1}] - R^F_{t,t+1}M_t\right)/S_t\right]$. □

B Description of variables

Relative bid-ask spread (BAS): We calculate the daily relative bid-ask spread as $BAS^i_d = (S^{ask,i}_d - S^{bid,i}_d)/(0.5(S^{ask,i} + S^{bid,i}))$. 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 (2002) illiquidity measure: We calculate daily Amihud's 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

$$
\begin{aligned}
ESF = {} & 0.07834 + 0.05438VRSI - 0.00664VRSI^2 + 0.000382VRSI^3 - 0.5908Option \\
& + 0.2587Option \cdot VRSI - 0.02713Option \cdot VRSI^2 L0.0007583Option \cdot VRSI^3,
\end{aligned}
$$

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).

Bali and Hovakimian's (2009) 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 Extended formula of CMER under option mispricing

In this section, we discuss how our option-implied CMER formula, Theorem 2.2, alters when we relax the assumption that options are not mispriced. Then, we empirically examine possible biases in option-implied CMER caused by frictions and associated mispricing in option prices. Specifically, we demonstrate that the inclusion of margin constraint in our model does not qualitatively changes our empirical findings.

C.1 Option-implied CMER formula under option mispricing

In Section 2, we assumed that there are no constraints on option trading (i.e., any constraint function $g_t^l(\boldsymbol{\theta}_t)$ does not contain $\theta_t^c(K)$ and $\theta_t^p(K)$) and hence option prices coincide with their respective fundamental price. When we relax this assumption, the first-order conditions for call and put options ($\theta_t^c(K)$ and $\theta_t^p(K)$) yield the following equations, respectively.

$$C_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1} - K)^+] + \sum_{l=1}^{L} \lambda_t^l \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)}, \tag{C.1}$$

$$P_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(K - S_{t+1})^+] + \sum_{l=1}^{L} \lambda_t^l \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}, \tag{C.2}$$

where the first term in equation (C.1) and (C.2) are the fundamental price of call and put, respectively. Due to the existence of market frictions, the market price and the fundamental price of options do not generally coincide. We denote the call and put fundamental prices by $C_t^*(K)$ and $P_t^*(K)$ to distinguish them from their market prices, $C_t(K)$ and $P_t(K)$. In this extended setup, Theorem 2.2 is generalized as follows:

Theorem C.1 *For any strike K, the following equation holds:*

$$CMER_{t,t+1} = \frac{R_{t,t+1}^0}{S_t}(C_t(K) - \widetilde{C}_t(K)) + \sum_{l=1}^{L} Z_t^l(K), \quad \textit{where} \tag{C.3}$$

$$Z_t^l(K) = -\frac{R_{t,t+1}^0}{S_t} \times \lambda_t^l \left(\frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)} \right). \tag{C.4}$$

Proof: See Appendix D.1. □

Theorem C.1 shows that when option prices can be mispriced, the option mispricing appears in CMER formula as an additional term as in the second term in the right hand side of equation (C.3). This additional term is given by the sum of Z_t^l, each of which represents the effect of l-th constraint and its associated mispricing in option prices on CMER. Equation (C.4) shows that, apart from the coefficient $-R_{t,t+1}^0/S_t$ which is common across any constraints, Z_t^l is the product of its Lagrange multiplier λ_t^l and $\frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}$. This difference of partial derivatives term denotes how l-th constraint function changes as the agent increases one unit of synthetic stock long position, where she goes long in a call option and short in a put option.

Theorem C.1 shows that the option-implied CMER we used in the main analysis (the first term in the right hand side of equation (C.3)) is an approximation of the true CMER when frictions on option trading and hence option mispricing exists. Even though research on options mispricing is still at its infancy compared to the literature on stock mispricing, recent literature demonstrates that at least the *margin constraint* affects option prices (see Santa-Clara and Saretto (2009) and Hitzemann et al. (2016)). Therefore, the margin constraint on option trading can also affect the calculation of CMER through a non-negligible Z_t^{mc} (the superscript mc stands for the *margin constraint*). In the next subsection, we estimate Z_t^{mc}. Then, we show that the inclusion of Z_t^{mc} does not qualitatively change our empirical findings.

C.2 Estimation of Z_t^{mc}: formula and empirical strategy

To assess the magnitude of Z_t^{mc}, we need to specify the margin constraint function g_t^{mc} and we also need empirical evidence on the magnitude of the Lagrange multiplier λ_t^{mc}. First, we follow Gârleanu and Pedersen (2011) to formalize the margin constraint function g_t^{mc} as follows:

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

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. (2016) for a detailed discussion):[24]

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

[24] Even though each option exchange can have a different margin rule, Hitzemann et al. (2016) document that the CBOE margin rule is the *de facto* standard margin rule in the U.S. option exchanges.

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

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

To simplify the calculation of the call and put margin rates, we restrict our attention to 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 Z_t^{mc}:

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

$$Z_t^{mc}(K) = R_{t,t+1}^0 \lambda_t^{mc} E_t(K), \quad \textit{where} \quad \text{(C.9)}$$

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

Proof: See Appendix D.2. □

We estimate $Z_t^{mc}(K) = R_{t,t+1}^0 \lambda_t^{mc} E_t(K)$ by relying on previous empirical evidence. To this end, we separately estimate $R_{t,t+1}^0 \lambda_t^{mc}$ and $E_t(K)$ and take their product. First, $R_{t,t+1}^0 \lambda_t^{mc}$ 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 $R_{t,t+1}^0 \lambda_t^{mc}$ if we extend our model to include both the collateralized and uncollateralized risk-free bonds.[25] Gârleanu and Pedersen (2011) find that the shadow cost of capital is time-varying and become higher during

[25]Let $R_{t,t+1}^u$ be the return of the uncollateralized bond and θ_t^u be the market-maker's position on the uncol-

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 $R^0_{t,t+1}\lambda^{mc}_t$. In the first specification, $R^0_{t,t+1}\lambda^{mc}_t$ 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 $R^0_{t,t+1}\lambda^{mc}_t$ as 5% per year (constant) considering the fact that 10% is the 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 $R^0_{t,t+1}\lambda^{mc}_t$ is given by the scaled TED spread, whose maximum value matches 10% per year during the financial crisis.[26]

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, recall that in our model there are two types of agents, the market-maker and the end-user. Let $d^c_t(K)$ and $d^p_t(K)$ be the end-user's demand for the call and put option, respectively. Then, at equilibrium, $d^c_t(K) = -\theta^c_t(K)$ and $d^p_t(K) = -\theta^p_t(K)$ hold because options are in zero net supply. Therefore, it follows that $sgn(\theta^c_t) = -sgn(d^c_t)$ ($sgn(\theta^p_t) = -sgn(d^p_t)$) in our equilibrium market model. We estimate the signs of the end-user's demand instead of the market-maker's position and take the opposite signs.

To infer the signs of the end-user's demand, we rely on Gârleanu et al.'s (2009) empirical

lateralized 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 $1 = \mathbb{E}^{\mathbb{P}}_t[m^*_{t,t+1}R^u_{t,t+1}] - \lambda^{mc}_t$. From these two first order conditions, we obtain $R^u_{t,t+1} - R^0_{t,t+1} = R^0_{t,t+1}\lambda^{mc}_t$.

[26]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 Z^{mc}_t.

finding in 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), i.e., the end-user buys (sells) the option:

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

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, i.e., 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.

To sum up, we estimate the Z_t^{mc}-adjusted CMER as follows:

1. First, we calculate options' expensiveness for each call and put options, where we calculate the difference between the BS-IVs and the one-year historical volatility, both of which are provided by the OM database.

2. Then, we estimate the signs of $\theta_t^c(K)$ and $\theta_t^p(K)$ for each pair of call and put options based on equation (C.11) and calculate $E_t(K)$ based on (C.10). There are three estimation results depending on the choice of the reference point value s.

3. Next, we multiply $E_t(K)$ and $R_{t,t+1}^0\lambda_t^{mc}$ to obtain Z_t^{mc} and calculate $R_{t,t+1}^0(C_t(K) - \widetilde{C}_t(K))/S_t + Z_t^{mc}(K)$. Since we examine three scenarios for $R_{t,t+1}^0\lambda_t^{mc}$, we obtain nine estimates of the Z_t^{mc}-adjusted CMER for each strike and maturity.

4. Finally, we construct monthly CMER by following the same procedure described in Section 3.2, but using the Z_t^{mc}-adjusted CMER constructed in Step 3 above.

Table A.1 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 Z_t^{mc}-adjusted CMER. The first column reports the baseline result shown in Section 4.2 (i.e., the case of the frictionless option market) and the remaining columns report the results for Z_t^{mc}-adjusted CMER-sorted portfolios, where Z_t^{mc} has been computed in nine different ways as described above. We can see that CMER predicts future stock returns cross-sectionally even when it is computed by relaxing the assumption of frictionless option markets (equations (C.3) and (C.4)). The average return and alphas are statistically and economically significant for each one of the nine alternative methods to compute Z_t^{mc}. This suggests that our baseline results are robust to the options' mispricing due to the presence of margin constraints on option trading.

[Table A.1 about here.]

D Proofs for Appendix C

D.1 Proof of Theorem C.1

The combination of equations (C.1) and (C.2) yields

$$C_t(K) - P_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^*(S_{t+1} - K)] + \sum_{l=1}^{L} \lambda_t^l \left(\frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)} \right). \tag{D.1}$$

The application of similar calculations to the ones required to prove equation (A.6) yields

$$C_t(K) - \widetilde{C}_t(K) = \mathbb{E}_t^{\mathbb{P}}[m_{t,t+1}^* M_{t+1} - M_t] + \sum_{l=1}^{L} \lambda_t^l \left(\frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^l(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)} \right). \tag{D.2}$$

Multiplying $R_{t,t+1}^0 / S_t$ to the both side of equation (D.2) proves equation (C.3). □

D.2 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

$$-\frac{1}{S_t}\left(\frac{\partial g_t^{mc}(\boldsymbol{\theta}_t)}{\partial \theta_t^c(K)} - \frac{\partial g_t^{mc}(\boldsymbol{\theta}_t)}{\partial \theta_t^p(K)}\right) = \frac{1}{S_t}\left[sgn(\theta_t^c(K))\mu_t^c(K)C_t(K) - sgn(\theta_t^p(K))\mu_t^p(K)P_t(K)\right], \quad \text{(D.3)}$$

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 (D.3) 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 (D.3) 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 (D.3) simplifies to

$$\frac{1}{S_t}\left[-(0.2S_t - (K - S_t)^+) + (0.2S_t - (S_t - K)^+)\right] = -\frac{S_t - K}{S_t}. \quad \text{(D.4)}$$

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 (D.3) is calculated as

$$\frac{1}{S_t}\left[C_t + (0.2S_t - (S_t - K)^+)\right] = 0.2 + [C_t - (S_t - K)^+]/S_t. \quad \text{(D.5)}$$

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 (D.3) is calculated as

$$-\frac{1}{S_t}\left[P_t + (0.2S_t - (K - S_t)^+)\right] = -\left(0.2 + [P_t - (K - S_t)^+]/S_t\right). \quad \text{(D.6)}$$

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

References

Acharya, V. V. and L. H. Pedersen (2005): "Asset Pricing with Liquidity Risk," *Journal of Financial Economics*, 77, 375–410.

Adrian, T., E. Etula, and T. Muir (2014): "Financial Intermediaries and the Cross-Section of Asset Returns," *Journal of Finance*, 69, 2557–2596.

Aït-Sahalia, Y. and A. W. Lo (1998): "Nonparametric Estimation of State-Price Densities Implicit in Financial Asset Prices," *Journal of Finance*, 53, 499–547.

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

An, B. J., A. Ang, T. G. Bali, and N. Cakici (2014): "The Joint Cross Section of Stocks and Options," *Journal of Finance*, 69, 2279–2337.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006): "The Cross-Section of Volatility and Expected Returns," *Journal of Finance*, 61, 259–299.

Asparouhova, E., H. Bessembinder, and I. Kalcheva (2013): "Noisy Prices and Inference Regarding Returns," *Journal of Finance*, 68, 665–714.

Asquith, P., P. A. Pathak, and J. R. Ritter (2005): "Short Interest, Institutional Ownership, and Stock Returns," *Journal of Financial Economics*, 78, 243–276.

Bali, T. G., R. F. Engle, and S. Murray (2016): *Empirical Asset Pricing: The Cross Section of Stock Returns*, Wiley.

Bali, T. G. and A. Hovakimian (2009): "Volatility Spreads and Expected Stock Returns," *Management Science*, 55, 1797–1812.

Battalio, R. and P. Schultz (2006): "Options and the Bubble," *Journal of Finance*, 61, 2071–2102.

Black, F. and M. Scholes (1973): "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy*, 81, 637–654.

Boehme, R. D., B. R. Danielsen, and S. M. Sorescu (2006): "Short-Sale Constraints, Differences of Opinion, and Overvaluation," *Journal of Financial and Quantitative Analysis*, 41, 455–487.

Brennan, M. J. and A. W. Wang (2010): "The Mispricing Return Premium," *Review of Financial Studies*, 23, 3437–3468.

Brunnermeier, M. K. and L. H. Pedersen (2009): "Market Liquidity and Funding Liquidity," *Review of Financial Studies*, 22, 2201–2238.

Carhart, M. M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

Chang, B. Y., P. Christoffersen, and K. Jacobs (2013): "Market skewness risk and the cross section of stock returns," *Journal of Financial Economics*, 107, 46–68.

Christoffersen, P., K. Jacobs, and B. Y. Chang (2013): "Forecasting with Option-Implied Information," in *Handbook of Economic Forecasting, Volume 2*, ed. by G. Elliiott and A. Timmermann, Elsevier, 581–656.

Cochrane, J. H. (2011): "Presidential Address: Discount Rates," *The Journal of Finance*, 66, 1047–1108.

Conrad, J., R. F. Dittmar, and E. Ghysels (2013): "Ex Ante Skewness and Expected Stock Returns," *Journal of Finance*, 68, 85–124.

Cox, J. C., S. A. Ross, and M. Rubinstein (1979): "Option Pricing: A Simplified Approach," *Journal of Financial Economics*, 7, 229–263.

Cremers, M. and D. Weinbaum (2010): "Deviations from Put-Call Parity and Stock Return Predictability," *Journal of Financial and Quantitative Analysis*, 45, 335–367.

Davis, J. L., E. F. Fama, and K. R. French (2000): "Characteristics, Covariances, and Average Returns: 1929 to 1997," *Journal of Finance*, 55, 389–406.

De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann (1990): "Noise Trader Risk in Financial Markets," *The Journal of Political Economy*, 98, 703–738.

Easley, D., M. O'Hara, and P. S. Srinivas (1998): "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade," *Journal of Finance*, 53, 431–465.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg (2017): "Short Selling Risk," *Journal of Finance*, forthcoming.

Fama, E. F. and K. R. French (1993): "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

——— (2015): "A Five-Factor Asset Pricing Model," *Journal of Financial Economics*, 116, 1–22.

Fama, E. F. and J. D. MacBeth (1973): "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81, 607–636.

Frazzini, A. and L. H. Pedersen (2014): "Betting Against Beta," *Journal of Financial Economics*, 111, 1–25.

Gabaix, X., A. Krishnamurthy, and O. Vigneron (2007): "Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market," *Journal of Finance*, 62, 557–595.

Gao, X. and J. R. Ritter (2010): "The Marketing of Seasoned Equity Offerings," *Journal of Financial Economics*, 97, 33–52.

Gârleanu, N. and L. H. Pedersen (2011): "Margin-based Asset Pricing and Deviations from the Law of One Price," *Review of Financial Studies*, 24, 1980–2022.

Gârleanu, N., L. H. Pedersen, and A. M. Poteshman (2009): "Demand-Based Option Pricing," *Review of Financial Studies*, 22, 4259–4299.

Giamouridis, D. and G. Skiadopoulos (2011): "The Informational Content Of Financial Options For Quantitative Asset Management: A Review," in *The Oxford Handbook of Quantitative Asset Management*, ed. by B. Scherer and K. Winston, Oxford University Press, 243–265.

Goncalves-Pinto, L., B. D. Grundy, and A. Hameed (2017): "Why Do Option Prices Predict Stock Returns ? The Role of Price Pressure in the Stock Market," FIRN Research Paper No. 2695145, Financial Research Network.

Greenwood, R. (2005): "Short- and long-term demand curves for stocks: Theory and evidence on the dynamics of arbitrage," *Journal of Financial Economics*, 75, 607–649.

Gromb, D. and D. Vayanos (2010): "Limits of Arbitrage: The State of the Theory," *Annual Review of Financial Economics*, 2, 251–275.

Hasbrouck, J. (2009): "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data," *Journal of Finance*, 64, 1445–1477.

He, H. and D. M. Modest (1995): "Market Frictions and Consumption-Based Asset Pricing," *Journal of Political Economy*, 103, 94–117.

He, Z., B. Kelly, and A. Manela (2017): "Intermediary Asset Pricing: New Evidence from Many Asset Classes," *Journal of Financial Economics*, 126, 1–35.

Hitzemann, S., M. Hofmann, and C. Wagner (2016): "Margin Requirements, Demand Pressure, and Equity Option Returns," SSRN Working Paper.

Hou, K., S. Kim, and I. M. Werner (2016): "(Priced) Frictions," Fisher College of Business Research Working Paper No. 2016-03-19, Ohio State University.

Hou, K. and T. J. Moskowitz (2005): "Market Frictions, Price Delay, and the Cross-Section of Expected Returns," *Review of Financial Studies*, 18, 981–1020.

Hou, K., C. Xue, and L. Zhang (2015): "Digesting Anomalies: An Investment Approach," *Review of Financial Studies*, 28, 650–705.

——— (2017): "Replicating Anomalies," NBER Working Paper No. 23394, National Bureau of Economic Research.

Jarrow, R. (2016): "Bubbles and Multiple-Factor Asset Pricing Models," *International Journal of Theoretical and Applied Finance*, 19, 1–19.

Jegadeesh, N. and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, 48, 65–91.

Kostakis, A., N. Panigirtzoglou, and G. Skiadopoulos (2011): "Market Timing with Option-Implied Distributions: A Forward-Looking Approach," *Management Science*, 57, 1231–1249.

Luttmer, E. G. J. (1996): "Asset Pricing in Economies with Frictions," *Econometrica*, 64, 1439–1467.

Manaster, S. and R. J. Rendleman (1982): "Option Prices as Predictors of Equilibrium Stock Prices," *Journal of Finance*, 37, 1043–1057.

McLean, R. D. and J. Pontiff (2016): "Does Academic Research Destroy Stock Return Predictability?" *Journal of Finance*, 71, 5–32.

Muravyev, D., N. D. Pearson, and J. M. Pollet (2016): "Is There a Risk Premium in the Stock Lending Market? Evidence from Equity Options," .

Nagel, S. (2012): "Evaporating Liquidity," *Review of Financial Studies*, 25, 2005–2039.

Ofek, E., M. Richardson, and R. F. Whitelaw (2004): "Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets," *Journal of Financial Economics*, 74, 305–342.

Santa-Clara, P. and A. Saretto (2009): "Option Strategies: Good Deals and Margin Calls," *Journal of Financial Markets*, 12, 391–417.

Shleifer, A. and R. W. Vishny (1997): "The Limits of Arbitrage," *Journal of Finance*, 52, 35–55.

Stambaugh, R. F., J. Yu, and Y. Yuan (2015): "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle," *Journal of Finance*, 70, 1903–1948.

Stambaugh, R. F. and Y. Yuan (2017): "Mispricing Factors," *Review of Financial Studies*, 30, 1270–1315.

Stilger, P. S., A. Kostakis, and S.-H. Poon (2017): "What Does Risk-Neutral Skewness Tell Us About Future Stock Returns?" *Management Science*, 63, 1814–1834.

Vayanos, D. and P. Woolley (2013): "An institutional theory of momentum and reversal," *Review of Financial Studies*, 26, 1087–1145.

Xing, Y., X. Zhang, and R. Zhao (2010): "What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns?" *Journal of Financial and Quantitative Analysis*, 45, 641–662.

Yan, S. (2011): "Jump Risk, Stock Returns, and Slope of Implied Volatility Smile," *Journal of Financial Economics*, 99, 216–233.

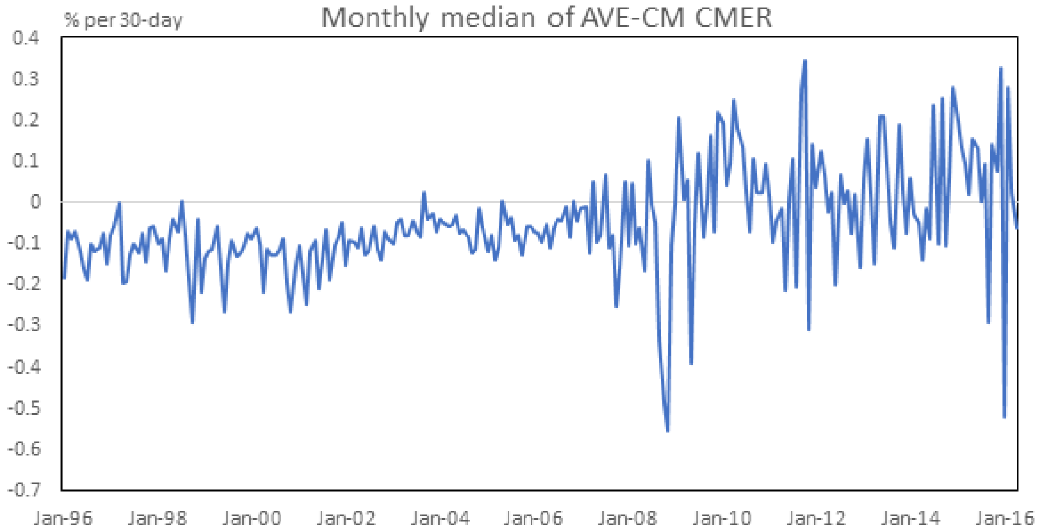

Figure 1. **Time Series of the monthly Median of AVE-CM CMER:** this figure illustrates the time-series of the monthly median of AVE-CM CMER. For each month, we calculate the median of the individual stocks' end of month AVE-CM CMER values. The unit of the y-axis is % per 30-day. The estimating period spans January 1996 to April 2016 (244 months).

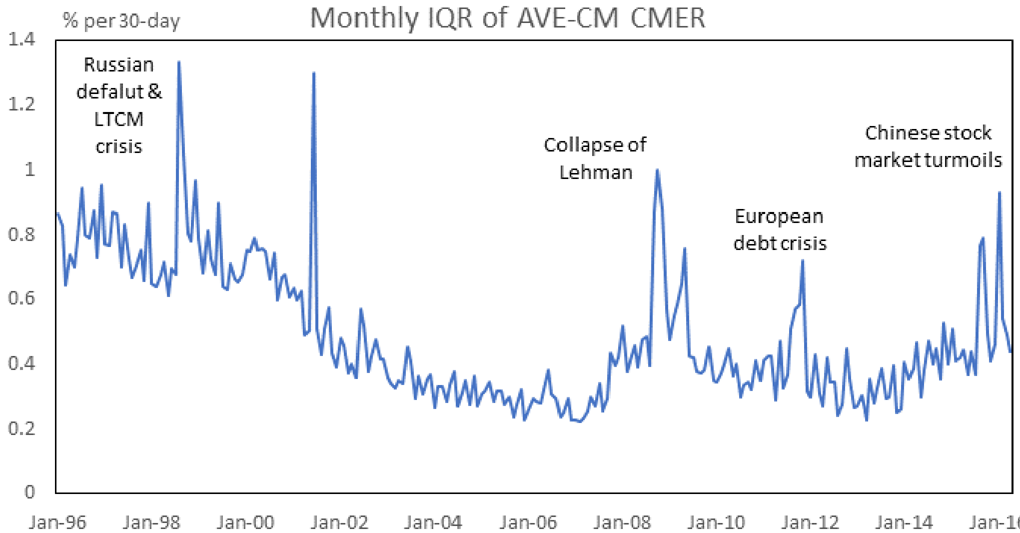

Figure 2. **Time Series of the monthly interquartile range (IQR) of AVE-CM CMER:** this figure illustrates the time-series of the monthly IQR (difference between the 75th and 25th percentile points) of AVE-CM CMER. For each month, we calculate the IQR of the individual stocks' end of month AVE-CM CMER values. The unit of the y-axis is % per 30-day. The estimating period spans January 1996 to April 2016 (244 months).

Table 1. Summary statistics of the estimated CMER

Entries in Panel A report the summary statistics of the estimated CMER on the end of each month for the four ways of estimating CMER. The estimation ways of CMER 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 CMER across available stocks, while in ATM methods, (2) and (4), we choose the strike closest to the forward price. In CM methods, (1) and (2), we interpolate traded maturities to obtain a 30-day constant maturity CMER, 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 CMER observations, the row for IQR reports the interquartile range (75th minus 25th percentile values), and the last row, % of $CMER > 0$, reports the proportion of observations with positively estimated CMER. The estimating period spans January 1996 to April 2016 (244 months). The unit of statistics (except skewness, kurtosis, and % of $CMER > 0$) is % per 30-day. Entries in Panel B report the pairwise Pearson correlation coefficients between the four estimated CMER.

Panel A: Summary statistics of the estimated CMER

	(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 CMER> 0	44.7%	44.9%	45.1%	45.4%

Panel B: Correlation between different estimation ways of CMER

	(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 CMER-sorted value-weighted and equally-weighted decile portfolios

Entries in Panel A report the average CMER, average post-ranking return and results for the risk-adjusted returns (α) of the AVE-CM CMER-sorted value-weighted decile portfolios and the spread portfolio, with respect to the CAPM and Carhart's (1997) four-factor model. On the last trading day of each month t, stocks are sorted in ascending order based on AVE-CM CMER 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 CMER, average post-ranking return and alphas of the AVE-CM CMER-sorted equally-weighted decile portfolios and the spread portfolio. The estimating 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 all variables is % per 30 days. N is the average number of stocks in each decile portfolio.

Panel A: Value weighted portfolios											
	AVE-CM CMER-sorted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Average CMER	-1.31	-0.53	-0.31	-0.18	-0.09	-0.01	0.07	0.18	0.36	0.93	2.24
Average 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											
Average CMER	-1.58	-0.55	-0.32	-0.19	-0.09	-0.01	0.07	0.18	0.37	1.14	2.73
Average 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. AVE-CM CMER-sorted decile Portfolios: Effect of Skipping First Trading Days

This table reports the monthly average returns and risk-adjusted returns (α_{FFC}) of the AVE-CM CMER-sorted value-weighted decile portfolios by skipping first trading days. Panel A reports results for the case where stocks are held from the close of the first date after the portfolio formation date. Panels B and C report the results, where we skip the first five and six trading days from the portfolio formation date, respectively. Portfolios are being formed based on the AVE-CM CMERs of the respective equities. The estimating period 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 30 days.

	AVE-CM CMER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
Panel A: The first trading day is skipped											
Average return	0.19	0.27	0.48	0.46	0.61	0.66	0.72	0.62	0.69	0.81	0.62
	(0.41)	(0.73)	(1.46)	(1.52)	(1.98)	(2.15)	(2.34)	(1.91)	(1.93)	(1.89)	(2.45)
α_{FFC}	-0.58	-0.38	-0.13	-0.06	0.04	0.10	0.16	0.14	0.16	0.27	0.86
	(-3.47)	(-2.39)	(-1.15)	(-0.59)	(0.36)	(1.01)	(1.48)	(1.30)	(1.06)	(1.50)	(3.56)
Panel B: The first five trading days are skipped											
Average return	0.21	0.38	0.49	0.38	0.47	0.45	0.52	0.50	0.43	0.73	0.51
	(0.60)	(1.21)	(1.97)	(1.76)	(2.01)	(1.88)	(2.19)	(1.91)	(1.62)	(2.02)	(2.13)
α_{FFC}	-0.42	-0.12	0.04	-0.04	0.06	0.01	0.07	0.12	0.00	0.23	0.65
	(-2.79)	(-0.72)	(0.36)	(-0.55)	(0.69)	(0.13)	(0.74)	(1.24)	(-0.01)	(1.32)	(2.67)
Panel C: The first seven trading days are skipped											
Average return	0.35	0.52	0.63	0.49	0.51	0.47	0.55	0.51	0.46	0.64	0.30
	(0.98)	(1.74)	(2.53)	(2.19)	(2.15)	(2.00)	(2.29)	(1.88)	(1.59)	(2.01)	(1.43)
α_{FFC}	-0.31	-0.04	0.10	0.03	0.07	-0.01	0.06	-0.03	-0.09	-0.03	0.27
	(-2.41)	(-0.31)	(1.18)	(0.44)	(0.86)	(-0.10)	(0.73)	(-0.33)	(-0.74)	(-0.23)	(1.38)

Table 4. Alphas of the regression of CMER-adjusted excess returns on risk factors

Entries in Panel A report the intercept (α) of the regressions of CMER-adjusted excess return $R_{t,t+1} - R^0_{t,t+1} - CMER_{t,t+1}$ on a set of risk factor(s) of 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 CMER and then value-weighted decile portfolios are formed. We then calculate the average CMER as well as the return in the succeeding month-$(t+1)$ of these portfolios and the spread portfolio to calculate the CMER-adjusted excess return. Entries in Panel B report the results of regressions, where we eliminate CMER observations below 1st percentile and above 99th percentile point. Entries in Panel C report the results of regressions, where we form quintile portfolios instead of the decile portfolios. The estimating period spans February 1996 to May 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 30 days.

	AVE-CM CMER-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 CMER											
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 CMER 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 CMER

	AVE-CM CMER-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 5. Characteristics of AVE-CM CMER-sorted value-weighted decile portfolios

Entries report the average value of various characteristics of decile portfolios as well as the difference between the highest CMER decile portfolio and the lowest CMER decile portfolio. On the last trading day of each month t, stocks are sorted in ascending order based on AVE-CM CMER 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 (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 CMER-sorted value-weighted decile portfolios										Spread
	1 (Lowest)	2	3	4	5	6	7	8	9	10 (Highest)	10-1
CMER	-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 6. Bivariate dependent sort on CMER: Controlling 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 CMER 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 CMER. Sixth to the last columns report the average returns, Fama and French (2015) five-factor alpha, and the average CMER, respectively of the spread portfolio between the highest CMER portfolio and the lowest CMER 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 estimating period ranges January 1996 to April 2016 (244 months)). t-statistics are adjusted for heteroscedasticity and autocorrelation (HAC-adjusted t-stat). The unit of all variables is % per 30 days.

	Ave. returns of AVE-CM CMER-sorted portfolios					Spread portfolio (5-1)		
	1 (lowest)	2	3	4	5 (highest)	Ave. return	α_{FFC}	Ave. CMER
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 7. Comparison between four estimation methods of CMER and removing extreme CMER samples

Entries in Panel A report the average return and Carhart (1997) four-factor model alpha of the spread portfolio of CMER-sorted value-weighted decile portfolios, where each column uses one of four estimation methods of CMER. 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 CMER, 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 CMER-sorted value-weighted portfolios. The first column shows the result, where we truncate AVE-CM CMER samples at 1% level, i.e., we remove CMER 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 CMER portfolio (portfolio 9) and short the second lowest CMER 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 CMER portfolio (portfolio 4) and short the second lowest CMER portfolio (portfolio 2). The estimating period ranges 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 α are % per month.

Panel A: Comparison between four estimation methods of CMER				
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 CMER 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 CMER: Controlling 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 CMER 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 CMER. The sixth to last columns report the average return, α_{FFC}, and the average CMER of the CMER-sorted spread portfolios, respectively. All returns are value-weighted returns. The estimating period ranges January 1996 to April 2016 (244 months)). The estimating period ranges 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 α are % per month.

	Ave. returns of AVE-CM CMER-sorted portfolios					Spread portfolio (5-1)		
	1 (lowest)	2	3	4	5 (highest)	Ave. return	α_{FFC}	Ave. CMER
$R_{t,-1,t}$ 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 Fama and French (2015) five-factor model alpha of the spread portfolio of AVE-CM CMER-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 αFFC of the AVE-CM CMER-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 αFFC of the AVE-CM CMER-sorted value-weighted decile portfolios, where we calculate decile portfolios' breakpoints based on NYSE stocks only. The estimating period ranges 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 α are % per month.

	AVE-CM CMER-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)											
Average 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											
Average 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											
Average 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. 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 CMER-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 30 days.

	AVE-CM CMER-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 CMER: Fama-MacBeth regressions

Entries report the results from Fama and MacBeth (1973) regressions of stock returns on AVE-CM CMER, market beta, SIZE (log of market equity), log of book-to-market, Momentum ($R_{t-12,t-1}$), previous month return $R_{t-1,t}$, idiosyncratic volatility, profitability (operational profit to book equity), investment (asset growth rate), Amihud's (2002) illiquidity measure, relative bid-ask spread and turnover rate. 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 CMER, respectively. Columns (8) and (9) report the results using only the observation over 1996-2006 and 2007-2016, respectively.

	All sample			NYSE/ AMEX	NASDAQ	$CMER \geq 0$	$CMER < 0$	1996–2006	2007–2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CMER	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 CMER, 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 CMER-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 30 days.

	Average return	α_{CAPM}	α_{FF3}	α_{FFC}	α_{FF5}	α_{SY}
CMER-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 estimated Z_t^{mc}-adjusted CMER

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 CMER-sorted value-weighted decile portfolios. The first column reports the baseline result of the AVE-CM CMER-sorted value-weighted decile portfolio for the sake of expediting the comparison. The second to the tenth columns report the results of the portfolio sort results based on nine alternative Z_t^{mc}-adjusted AVE-CM CMER. Each one of the nine alternative CMER is characterized by the assumption on $R^0_{t,+1}\lambda_t^{mc}$ 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. The unit of all variables is % per 30 days.

	baseline	$R^0_{t,t+1}\lambda_t^{mc} = 10\%$ per year			$R^0_{t,t+1}\lambda_t^{mc} = 5\%$ per year			Time-varying $R^0_{t,t+1}\lambda_t^{mc}$		
	result	$s = 0.00$	$s = 0.01$	$s = 0.02$	$s = 0.00$	$s = 0.01$	$s = 0.02$	$s = 0.00$	$s = 0.01$	$s = 0.02$
Average return	1.64	1.58	1.61	1.73	1.57	1.63	1.69	1.60	1.60	1.64
	(5.77)	(5.28)	(5.42)	(5.58)	(5.46)	(5.52)	(5.54)	(5.50)	(5.54)	(5.59)
α_{CAPM}	1.70	1.64	1.66	1.79	1.63	1.69	1.76	1.66	1.66	1.71
	(5.91)	(5.30)	(5.36)	(5.49)	(5.55)	(5.42)	(5.61)	(5.65)	(5.70)	(5.74)
α_{FF3}	1.78	1.75	1.77	1.89	1.71	1.79	1.86	1.74	1.74	1.79
	(6.36)	(5.95)	(5.99)	(6.03)	(6.14)	(5.97)	(6.15)	(6.20)	(6.24)	(6.24)
α_{FFC}	1.86	1.83	1.85	1.97	1.76	1.85	1.93	1.78	1.78	1.82
	(6.56)	(6.16)	(6.25)	(6.35)	(6.09)	(6.28)	(6.43)	(6.18)	(6.19)	(6.16)
α_{FF5}	1.58	1.49	1.50	1.65	1.49	1.53	1.62	1.49	1.50	1.55
	(5.63)	(5.45)	(5.56)	(5.66)	(5.54)	(5.46)	(5.63)	(5.42)	(5.46)	(5.55)
α_{SY}	1.70	1.63	1.65	1.78	1.56	1.65	1.76	1.56	1.57	1.62
	(5.21)	(4.84)	(4.94)	(5.07)	(5.12)	(4.95)	(5.20)	(5.09)	(5.15)	(5.20)