Capital Market Consequences on CDS Mispricing*

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Abstract

This paper investigates impacts of CDS pricing errors (CPEs) on different capital markets. I find that CPEs can significantly predict future CDS returns reversal. Consistent with mispricing channel, the predictability of CPEs is particularly strong for CDS contracts with poor liquidities and for periods with high macro-uncertainty. Further analysis shows that CPEs temporarily drive not just future returns dynamics of stocks and put options contracts but also future stock volatility shocks (leverage effect). However, CPEs exhibit almost no predictive powers for returns dynamics of corporate bonds and call options contracts. Importantly, the predictability pattern of stock returns strongly reverses after 15 days suggesting that arbitrageurs trade oppositely to correct mistakes when they realize that short-run CDS price changes are in fact due to price errors rather than changes in fundamentals. The evidence thus implies that trading interactions among different capital markets will sometimes reduce the overall price informativeness. Collectively, this paper provides one of simple way to look at complex capital markets interactions and has addition insight on market efficiencies.

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1 Introduction

Merton (1974) developed a structure framework to study fundamentals of prices of distress risk under risk-neutral world. Collin-Dufresne et al.(2001) introduced a parsimonious empirical approach to investigate theoretical predictions of the structure model. In particular, they used the structural approach to identify empirical proxies of theoretical determinants of credit risk and regressed change of credit spread on the determinants. They focused on R^2 of the linear models. Since then, a substantial body of empirical works attempted to verify predictions of structure frameworks followed by Collin-Dufresne et al.(2001)s' approach (see, for example, Campbell and Taksler (2003); Cremers et al. (2004); Ericsson, Jacobs, and Oviedo (2009); Tang, and Yan (2012); Galil et al. (2014); Bai and Wu (2016), among many others' studies). Ericsson, Jacobs, and Oviedo (2009) found that stock volatility, market leverage, and 10-year treasury yield can explain 50%-60% variations in CDS spreads from 1999 to 2002. Kapadia and Pu (2012) conducted a similar analysis using a two-factor model including equity volatility and market leverage. They found that 56% of variations in CDS spreads are explained from 2001 to 2009 based on 214 firms. More recently, Bai and Wu (2016) combined distance-to-default measure with a long list of firm fundamentals using a Bayesian shrinkage approach and find an average R^2 of 77% in CDS spreads for 579 firms over 351 weeks from Jan 2003 to Sep 2009.

This article evaluates 5-year CDS spreads using Collin-Dufresne et al. (2001)s' valuation framework and finds that valuation errors significantly predict future (5-year) CDS returns - using an out-of-sample long-short strategy between past the most undervalued CDS and past the most overvalued CDS, I find that a large CDS profit in daily, weekly, and monthly frequency. This suggests existence of either mispricing or model misspecification. I investigate possible explanations and conclude that the predictive result is consistent with CDS illiquidity and macro-uncertainty. Thus is consistent with mispricing channel.

I begin with valuing 5-year CDS spreads using OLS for 887 firms from 2001 to 2015. I define CDS pricing errors (CPEs) as whether realized CDS spreads are either overvalued or undervalued by markets relative to benchmark models[1]. In order to reduce the concern that the results may be

[1] This is considered as how much realized CDS spreads deviate from model generated spreads. Overvalue is

driven by one particular specification of CDS valuation model, I employ three different specifications to measure pricing errors of credit spreads[2]. The first model is based on firm-by-firm time-series regression[3] in the spirit of Ericsson, Jacobs, and Oviedo (2009) (EJO, hereafter). The next two models are based on cross-sectional regression in the spirit of Kapadia and Pu (2012) and Bai and Wu (2016). In particular, the three specifications are listed below:

- Model 1, time-series: regressing 5-year CDS spreads on an intercept, the amount of market leverage incurred by the underlying firm, the stock volatility of the underiying firms, and the 10-year treasury rate firm by firm[4].
- Model 2, EJO cross-section 1: regressing 5-year CDS spreads on an intercept, market leverage, stock volatility date by date.
- Model 3, EJO cross-section 2: regressing 5-year CDS spreads on an intercept, market leverage, stock volatility, individual stock prices, M/B ratio, ROA, market capitalization, corporate cash holding date by date.

The CPEs are computed as residuals of the above three models. Even if arbitrage risks can defer efficient price movement of CDS markets as discussed in some papers such as Tang and Yan (2012) and Kapadia and Pu (2012), market frictions do not explicitly contribute to fundamental drivers of financial distress according to structure frameworks. Thus rather than including arbitrage risks such as illiquidity in the above models, I separately investigate impacts of arbitrage risks on capital market outcomes of CPEs.

I conduct a cross-sectional portfolio sorting approach by ranking CDS returns at t+1 based on CPEs at t and I find that undervalued CDSs yield positive next 1-day, 1-week, and 1-month returns while an overvalued CDSs yield negative next 1-day, 1-week, and 1-month returns. Buying under-

classified as when realized spread is greater than model generated spread. Undervalue is classified as when realized spread is smaller than model generated spread.

[2]My strategy of model selection includes: I consider EJOs' three-factor model as the benchmark and then include different variables suggested by recent literature on top of the benchmark. This is because these factors are theoretically motivated and empirically proved to be useful (in terms of high R^2) to value CDS spreads.

[3]Time-series estimation framework may have unit root problem since the left hand side variable is CDS level, which may be non-stationary. To check this, I apply augmented dickey-fuller test to confirm that majority of pricing errors are stationary or I(0). Furthermore, even if CPEs are non-stationary or I(1), it should not affect my results because unit root only introduces problem when one attempts to draw statistical inference based on slope coefficients. However, the goal of this paper is to look at the impact of CPEs on real economic outcomes.

[4]This is done by using recursive estimation progress considering first 252 days observations as initial estimation sample. The recursive estimation is to control for look-ahead bias or trying not to overstate the portfolio performance in the latter out-of-sample investment design. Sample of CPE of model 1 is from 2002 to 2015.

valued CDSs and selling overvalued CDSs in next 1-day, 1-week, and 1-month generates consistently large and significant amounts of profits. This is consistent with the logic of short/long leg portfolio in empirical asset pricing literature. It states that abnormal profits will emerge if one short (buy) the overvalued (undervalued) assets in short (long) leg of anomaly portfolios (Stambaugh, Yu, and Yuan (2012), Stambaugh, Yu, and Yuan (2015), and Stambaugh and Yuan (2016)). The results are robust to different sample periods, alternative CPE measures, different credit rating groups, are pervasive to different industries groups and various clause terms[5].

Whether the existence of these large investment profits are because of omit variable bias or mispricing? I investigate potential explanations. Firstly, using an independent double sort of CPE and CDS illiquidity, which is proxied by (1) number of contributions that provide quotes to Markit and (2) the proportion of zero CDS prices changes over total number of non-zero CDS price changes over the past 30 days, I find that large amounts of variations in CPE profits are explained by CDS liquidity. It suggests that CPE carries a liquidity premium. Secondly, by splitting CPE portfolio returns into high uncertainty regime and low uncertainty regime[6], I find that profits of CPE portfolio are driven by the high uncertainty regime. This suggests that macro-uncertainty affects the trading of CDS via influencing ambiguity-averse investors' perceptions given valuation.

Mispricing should serve as good explanation for the findings. The large liquidity premium is consistent with the sources (market frictions and funding constraints) of existence of mispricing. This evidence is consistent with Lewis, Longstaff, and Petrasek (2017) who use a unique dataset to directly test for asset mispricing and emphasize that dealers' funding constraints and liquidity of the underlying securities. Indeed, CDS markets should lack of price efficiency compared with stock markets due to its unique market feature: price discovery accomplishes with matching sessions. For example, Collin-Dufresne, Junge, and Trolle (2016) find that matching sessions and workups account for over 70% of trading volume on GFI. Duffie and Zhu (2016) theoretically show that the matching frictions can cause costly price delays. Also CDS markets are expected to have poor liquidity compared with stock markets suggested by Hilscher, Pollet, and Wilson (2015).

Next I investigate the implication of CPE on other capital markets such as stocks, bonds, and

[5]I keep all the additional test in Appendix, which is available upon request.

[6]The uncertainty is proxied by VIX, CFSI, and EPU respectively.

options markets. CPEs should not affect other capital markets returns at all if either they work independently or they figure out that CDS price movements are just pricing errors. Alternatively, spillover effects from CPEs to other markets should suggest that they do not immediately realize that CDS price reactions are in fact price errors. As such, it is likely that they move conditional on the transitory CDS price changes caused by future CPEs corrections.

I find that CPEs can predict subsequent days and weeks' cross-sectional stock returns. Since CPEs serve as a powerful predictor for future CDS returns and future CDS returns should negatively correlate with future stock returns[7], low (high) CPE predict the low (high) future stock returns. The predictability, however, significantly reverse after 15 days. The reversion lasts for another 15 days. It suggests that stock markets do ride on CDS price errors but they stop to do so and even trade inversely when they realize that they are wrongly riding on price errors. It causes market inefficiency, which is consistent with the point that trading interactions among capital markets reduce price informativeness (Goldstein, Li, and Yang (2013)).

I also find that CPEs can negatively predict returns of out-of-money puts. Similar to the intuition of return predictability in the case of stocks, the negative predictive powers of CPE are consistent with the view that puts markets ride on CDS mispricing. The empirical evidence suggests that out-of-money puts and CDS returns are tightly linked that support the structure pricing framework combining two financial derivatives developed by Carr and Wu (2010). My result also relates to the point that puts options can potentially allow arbitrageurs to spread bad credit news across various contracts in the sense of hiding their trading strategies.

I find that CPEs exhibit almost no predictive ability on corporate bonds and call options returns. On the one hand, U.S. corporate bonds markets are dominated by institutional investors who suppose to have better understanding on the value of outstanding corporate debts, thus they are more likely to detect whether the current CDS prices are inflated or deflated relative to underlying bonds. On the other hand, even though there may exist a set of speculators who bet on CDS mispricing and selectively proceed the above information in a more capital liquid market, both stocks and options markets are supposed to be better trading venues compared with corporate bond markets. The weak return predictability on return of calls suggest the two markets are

[7]The negative correlation between stocks and CDS returns are implied by contingent claim analysis.

loosely linked.

Additionally, CPE negatively predicts future stock volatility. This is a potential resolution of the debate on leverage and volatility feed hypothesis. The stock volatility is computed using intra-day stock transaction prices. This is to mitigate the concern of model risk when one estimate volatility using daily data. I run regression of future changes of stock volatilities on past changes of CPE and I find that changes of past CPE predict future volatilities. In addition, this result remains robust when past stock returns, dollar volumes and effective spreads are controlled. The result is explained by strong predictability of CPE reversal: undervalued (overvalued) CDS should predict future higher (lower) CDS spreads. This is because increasing (decreasing) CDS spread should increase (decrease) the capital structure of firms. If CPE can predict CDS price changes, it should raise (decrease) future stock volatilities. This empirical evidence helps to distinguish leverage effect hypothesis from volatility feedback hypothesis since CPE overcomes the empirical challenge using stock returns to predict future volatility.

Capital markets underlying corporations evolute rapidly over time, not only for sizes but also for types. At the same time, they are segmented. The co-existence of various segmented financial markets places complexities to digest their fundamental linkages. For instance, different markets hold different opinions and trade motivations on the identical firm-specific information source and it may lead to different trade outcomes. It, sometimes, goes beyond limit-to-arbitrage. There are numerous of theoretical works connecting to this point (e.g., Easley, O'Hara, and Srinivas(1998), Goldstein, Li, and Yang (2013), Duffie and Zhu (2017) etc.). To extent of my knowledge, this is the first empirical study to look at pricing errors spillover among capital markets and discuss their implications in very detail. I look at whether, how, and why, the market imperfection from one market spillover to the other. The empirical results have important implication on market efficiency and provide a simple way to look at the complex interactions among different capital markets.

This study also relates to numerous papers explaining the credit spread using Collin-Dufresne et al.(2001)s' approach. This paper finds that increasing in the explanation power of the valuation model needs not to be associated with enhancing efficiency of the asset prices underlying the model. It suggests more powerful test designs such as portfolio sorting needing to be adopt when one draw implication on explanation power of model. This sheds new light on the large set of existing literature using Collin-Dufresne et al. (2001)s' empirical approach to value CDS spreads (See, for example, Campbell and Taksler 2003; Cremers et al. (2004); Ericsson, Jacobs, and Oviedo (2009); Tang, and Yan (2012); Galil et al. (2014); Bai and Wu (2016)).

A similar paper by Jarrow, Li, Ye, and Hu (2018) conduct statistical arbitrages based on price discrepancies along CDS term structure and show that a large amount of profit can be generated: annualized returns about 71.5% with annualized Sharpe Ratio 7.8. This paper focuses on the capital market implications of CPE on not just CDS markets, but also other financial markets based on a larger number of firms over longer sample periods and has broader implication on capital market efficiency (Norden andWeber (2004), Acharya and Johnson (2007), Qiu and Yu (2012), Ni and Pan (2011), Fonseca, Gottschalk (2012), and Hilscher, Pollet, and Wilson (2015) and Marsh and Wagner (2016), Bai, Hu, Liu, and Zhu (2017), Kryzanowski, Perrakis, and Zhong (2017) and Lee, Naranjo, and Velioglu (2017)) and adds to the leverage effect studies (Black (1976), Christie (1982), Figlewski and Wang (2000), French et al., (1987), Campbell and Hentschel (1992), Aggarwal and Zhao (2007), Hens and Steude (2009), Hasanhodzic and Lo (2011), Carr and Wu (2011), Ait-Sahalia, Fan, and Li (2013), and Choi and Richardson (2016)). In addition, in terms of empirical methodology, I adopt the parsimonious approach introduced by Collin-Dufresne et al.(2001) to do the CDS valuation rather than using reduced-form estimation approach. It has two advantage: (1) The Collin-Dufresne et al.(2001)s' approach is more easier to implement compared with reduce-form approach used in Jarrow, Li, Ye, and Hu (2018); (2) the default probability embedded in CDS spreads can be exactly identified.

The remainder of the paper is layout as follows. Section 2 describes the data and sample. In section 3, I measure CPE. Section 4 shows that CPEs predict future CDS returns and section 5 studies the economic interpretation of section 4. Section 6 studies the capital markets implication of CPE. Section 7 concludes.

2 Data

2.1 Sample

The CDS spread data used in this paper are from Markit over period from 2001[8] to 2015. I obtain daily CDS spread data and number of contributors for five-year CDSs on senior, unsecured debt, and use modified restructuring default clause before April 2009 and use no restructuring clause afterward.[9] of non-government firms. The credit rating data is provided by Markit that is an average of the Moody's and Standard & Poor's (S&P) credit ratings adjusted to the seniority of the instrument and rounded to not include the "+" and "-" levels[10]. I match CDS data with Center for Research in Security Prices (CRSP) database to obtain daily stock returns, closing stock prices, and number of shares outstanding [11]. The accounting fundamental information is obtained from COMPUSTAT. I merge accounting dataset to stock/CDS dataset based on earnings announcement date (RDQ). I fill the missing value using the past observations for the most recent quarters. The bond transaction data is obtained from Trace and the option tranaction data is obtained from OptionMetrics. The other dataset includes Fama-French data library from Professor French's personal website[12].To ensure sufficient data for the estimation of CDS pricing errors, I require that each firm panel must have at least 1-year (252 days) trading data. I apply a filter to remove stale price observations, where I define prices to be stale when I observe equal prices on at least have 5 consecutive days. In such a case, I only consider the first of these observations and classify subsequent observations as not available.Thus my final sample covers 1781,846 firm-day observations for 887 firms with both traded stocks and CDSs from 2001 to 2015.

[8] The sample begins in Jan 2001 because Markit group starts since Jan 2001.

[9] I follow Hilscher, Pollet, and Wilson (2015) to restrict the CDS by modified restructuring default clause before April 2009 CDS "big bang" because this is the restructuring convention that is most commonly used for U.S. firms. I follow Lee, Naranjo, and Guner (2017) requiring no restructuring clause afterward.

[10] Additionally, we also use alternative rating obtained from Compustat rating file to split the sample.

[11] I combine CRSP and Markit primarily using first 6 digit CUSIP. For the rest of firms cannot be matched using CUSIP number, I conduct a manually match across two databases by using long-legal names.

[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

2.2 Stock and CDS returns

I compute the 5 Year CDS daily return or credit protection return by percentage change in credit spreads. The increase of credit return reflects the loss of the credit protection seller. Noted by Hilscher, Pollet, and Wilson (2015), credit returns should equal to the percentage change in the quoted CDS spread adjusted by the ratio of two annuity factors. However, in practice, the percentage change of spread is well proxy for CDS protection return because the annuity ratio will always be close to 1. Thus we use the percentage change of CDS protection return in our empirical analysis. Papers use percentage change in credit spreads as proxy for credit returns including Kapadia and Pu (2012) and Hilscher, Pollet, and Wilson (2015). Stock returns are computed as stock price changes including dividends and adjusted for share splits .

2.3 Firm Characteristics

- **Stock Volatility**: Time series of equity volatility is computed for each firm using an exponentially weighted moving average (EWMA, hereafter) model on daily returns obtained from CRSP following Ericsson, Jacobs, and Oviedo (2009). In particular, for each firm, volatility $\sigma_{i,t}$ is generated according to $\sigma_{i,t} = r_{i,t}^2(1-\lambda) + \sigma_{i,t-1}\lambda$, where λ is fixed at 0.95 following RiskMetrics produced by JP Morgan.
- **The market leverage ratio**: Followed by Ericsson, Jacobs, and Oviedo (2009), the leverage ratio is computed as

$$\text{Lev} = \frac{\text{Book Value of Debt+Book Value of Preferred Equity}}{\text{Market Value of Equity+Book Value of Debt+Book Value of Preferred Equity}}$$

  The Market value of equity is computed as number of shares outstanding (SHROUT) multiply by stock prices (PRC) from CRSP. The data of book value of debt and the book value of preferred equity is obtained from COMPUSTAT. Book value of debt is the sum of debt in current liability (DLCQ) and long-term debt (DLTTQ). Preferred stocks are labeled as PSTKQ in COMPUSTAT.
- **10-year Treasury Bond Yields**: Daily frequencies of 10-year Treasury bond yields are collected from DataStream. This is a constant maturity index constructed by the U.S. Treasury

based on the most actively traded issues in the 10-year maturity segment.

- **Term Spread**: The term spread is computed as the difference between 10-year Treasury Bond Yields and 3-month Treasury bill yields. They are in daily frequency and collected from DataStream.
- **EPS**: EPS (EPXPXQ) is earnings per share (basic) by excluding extraordinary items. This is in terms of quarterly frequency and is obtained from COMPUSTAT.
- **Cash**: This is defined as cash and cash equivalent over market value of total assets at quarterly frequency. Cash is cash and short-term investment used as CHEQ. The market value of total asset is computed as the sum of total liabilities and market values of equity (LTQ+PRC*SHROUT/1000). This is in terms of daily frequency and is obtained from COMPUSTAT/CRSP. Total liability is labeled as LTQ in COMPUSTAT. Stock price and number of shares outstanding are labeled as PRC and SHROUT in CRSP.
- **M/B ratio**: The M/B or market to book ratio is computed as the ratio of market value of equity and book value of equity: MB=(PRC*SHROUT/1000)/(CEQQ+TXDITCQ-PSTKQ). This is in terms of daily frequency and is obtained from COMPUSTAT/CRSP. TXDITCQ is deferred taxes and investment tax credit. PSTKQ is preferred stocks.
- **ROA**: The ROA or returns on total asset. This is computed as the ratio of EBIT and total asset: ROA=IBQ/(LTQ+PRC*SHROUT/1000). IBQ is EBIT in COMPUSTAT.
- **Corporate Liquidity**: The corporate liquidity is computes as ratio of working capital (WCAPQ, in balance sheet) and total asset.
- **Market Size**: the market value of the equity of the firm (PRC $\times$ SHROUT).

2.4 Proxies for Macro-Level Uncertainty

- **VIX**: VIX measures market expectation of near term volatility conveyed by stock index option prices. The index is at daily frequency for U.S. market. The data is available at Professor Ludvigson's website: https://www.sydneyludvigson.com/data-and-appendixes/.
- **Policy Uncertainty Index**: The policy uncertainty index (PU) is constructed by Baker, Bloom, and Davis (2016) that including three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. A second com-

ponent reflects the number of federal tax code provisions set to expire in future years. The third component uses disagreement among economic forecasters as a proxy for uncertainty. The index is at daily frequency for U.S. market. The data is available at https://fred.stlouisfed.org/series/USEPUINDXD.

- **Cleveland Financial Stress Index (Credit Sector)**: The Cleveland Financial Stress Index (CFSI) is developed by Federal Reserve Bank of Cleveland. It incorporates information from a number of financial markets to provide a measure of financial system stress on a continuous basis. Here, I consider only the contribution to credit markets. The data is available at https://fred.stlouisfed.org/series/CMRKTSD678FRBCLE[13].

[Table 1 about here]

2.5 Descriptive Statistics

Table 1 reports the summary statistics of the variables used in the analysis. In the first column of Panel A, I pool the 1781,846 firm-day observations and compute the sample average from 2001 to 2015. The sample average of 5-year CDS spreads is about 167.5 bps. In general, the sample consists of large firms (the average stock market size is about 19819 million) with moderate market leverage (mean is about 0.37). In addition, my sample of firms are profitable (11.5 EPS and 0.497 ROA) with average rating about BBB and have reasonable amount of corporate liquidity.

I divided each variable into 5 quintile groups based on 5-year CDS spread levels and compute the sample average for each CDS quintile. Small indicates the quintile with the smallest CDS spreads, 2 indicates the second smallest so on so forth. The average CDS levels at the 5 quintiles are 34.4, 59.6, 91.6, 158.6, and 492.9 bps. The ratio of the fifth quintile over the fourth average CDS spread is about 3.11 (492.9/158.6), which is about three times larger than that of the second quintile over the first quintile. It suggests the distribution of the CDS spreads is positively skewed.

In terms of firm characteristics at different CDS quintiles reported in column (2) to (6), I find

[13] For more detail information on the index please refer to https://www.clevelandfed.org/newsroom-and-events/publications/economic-commentary/economic-commentary-archives/2012-economic-commentaries/ec-201204-the-cleveland-financial-stress-index-a-tool-for-monitoring-financial-stability.aspx.

that there is a monotonic increasing pattern (respect to CDS quintiles) in Market leverage, stock volatility, stock returns, Net working capital, corporate cash holding, and rating; there is a decreasing pattern in stock price, EPS, M/B ratio. This is consistent with a view that firms with high CDS spreads are associated with high distress risk and correlated with high stock risks and returns.

Panel B examines how those characteristics different across firms and time as well as how correlated with CDS spreads. Column (1) is the cross-sectional standard deviation where I estimate the cross-sectional standard deviation for each variable each date and report the time-series averages of the cross-sectional estimates. Column (2) is the time-series standard deviation where I estimate the time-series standard deviation for each firm and report the cross-sectional average of these estimates. I observe that almost all the firm characteristics, cross-sectional standard deviations are much larger than time-series standard deviations[14]. This is consistent with finding of Bai and Wu (2016) suggesting that anchoring firm fundamental characteristics to value credit spreads.

3 CDS Pricing Errors

3.1 Measuring CDS Pricing Errors

In this section, I generate empirical valuation on 5-year CDS spreads and obtain the pricing error as residuals of the valuation model. In order to reduce the concern that results may be driven by one particular specification of CDS valuation model, I employ three different specifications to measure pricing errors of credit spreads. The first model is based on firm-by-firm time-series regression in the spirit of Ericsson, Jacobs, and Oviedo (2009). In particular, I have

$$\ln \mathrm{CDS}_{i,t} = \alpha_i^{\tau} + X_{i,t}\gamma_{\tau} + \epsilon_{i,t}^{\tau} \tag{1}$$

where $X_{i,t}$ is a t by k matrix and γ_τ is k by 1 vector. X contains Ericsson, Jacobs, and Oviedo (2009)s' three factors such as market leverage, firm-level volatility, and 10-year Treasury yield. Since from Table 1, CDS spread is positive skewed. I take the natural logarithm of the CDS spreads for the sake of better distributional behavior. Additionally, the estimation is conducted

[14]except stock returns, stock volatility.

recursively (use information up to t) without using future information to value CDS spreads at t. I use first 252 daily data as initial estimation sample. The first pricing error is thus computed as:

$$\mathrm{CPE1}_{i,t} = \mathrm{CDS}_{i,t} - \exp\{\alpha_i^\tau + X_{i,t}\gamma_\tau\} \tag{2}$$

I denote the first CDS pricing errors as CPE1. The second and third models are cross-sectional model in the spirit of Kapadia and Pu (2012) and Bai and Wu (2016). The specification is defined as

$$\ln \mathrm{CDS}_i = \alpha + X_i\lambda + \epsilon_i, \text{for all t} \tag{3}$$

where in my second specification, X include stock volatility and market leverage. Cross-sectional pricing errors is computed as CPE2 = $\mathrm{CDS}_{i,t} - \exp\{\alpha_i + X_{i,t}\lambda\}$. In my third specification, I combine stock volatility and market leverage with other firm fundamental variables including EPS, Cash, M/B, ROA, Market size, Corporate liquidity. The pricing errors of the third model are thus defined as CPE3.

To ensure the pricing errors convey different information from the CDS spread level, I conduct an alternative measure of CPE by standardizing CPE by the CDS spread level:

$$\text{Alternative } \mathrm{CPEj}_{i,t} = \frac{\mathrm{CPEj}_{i,t}}{\text{CDS Spread}_{i,t}} \tag{4}$$

where j=1,2,3; i indicates firm and t indicates day.

3.2 Descriptive Statistics for CDS Pricing Errors

Table 2 reports the summary statistics for adjusted R^2 and CPE across above three models.

[Table 2 about here]

In Panel A of Table 2, I compare the average adjusted R^2s across three different models. The model 1 is firm by firm time-series estimation of expected CDS spreads using stock volatilities, market leverage, and 10-year treasury yields based on Eqs.(1). The model 2 & 3 are cross-sectional regression estimation of expected CDS spreads using stock volatilities, market leverage and stock volatilities, market leverage plus a set of fundamental variables.

The model 1 (firm by firm time-series model) produces larger adjusted R^2 than the cross-sectional model. Specifically, the average adjusted R^2 of the first model is 58.24%, which is larger than these of model 2 & 3 with adjusted R^2 about 29.7% and 36.1% respectively. This lower adjusted R^2s of cross-sectional model 2 & 3 are consistent with the larger cross-sectional variations reported in Table 1. The R^2s of model 1, however, are more volatile (about 21.54%) than those of model 2 & 3 (about 7.55% and 5.70%), suggesting that the cross-section models generate lower estimation errors. Comparing two cross-sectional models, model 2 & 3, although model 3 consists six more explanatory variables than model 2, the average adjusted R^2 of model 3 is 7% larger than that of model 2.

The average R^2 from cross-sectional estimate of CDS spreads is on average smaller than these reported in Panel A of Table 2 of Bai and Wu (2016): 49%. This may due to different frequencies between two studies to conduct the estimation: weekly frequency used in Bai and Wu (2016) and daily frequency used in this study. Interestingly, I conduct a trading strategy exploited CPE based on various specifications and I find that the profits are not monotonically decline as R^2 increases. It suggests that increasing in the explanation power of valuation model needs not to be associated with enhancing efficiency of the asset prices underlying the model. See Section 4.2 for more results and discussions.

Panel B of Table 2 reports the sample means and sample standard deviations (pooling estimate, reported in the brackets) of CPE across three different models. Like Table 1, I partition the sample by CDS spreads into quintiles. I find that small CDS spreads are associated with negative pricing errors (suggested underpriced), whereas large CDS spreads are associated with positive pricing errors. CPE1 generates smaller magnetite of pricing errors compared with CPE2 and CPE3. In addition, CPEs are positive skewed. For example, the ratios of CPE between the fifth CDS quintile and the fourth CDS quintile are ranging from 5 to 9 times that is much larger than that computed from the second and the first CDS quintile.

4 Credit Default Swaps Price Errors Reversals

In this section, I examine whether overpriced (underpriced) CDS will generate lower (higher) returns in the future. In efficient markets, the pricing errors should not predict future asset returns. Any evidence against this point may suggest market inefficiency. Specifically, returns tend to be positive after investing in underpriced asset and negative after investing in overpriced asset - in order words, assets are seemingly priced wrongly at t will sluggishly adjust back to their fair value in future. The empirical asset pricing literature find that the abnormal profit will emerge if one short (buy) the overpriced (underpriced) stocks in the short (long) leg of anomaly portfolios (Stambaugh, Yu, and Yuan 2012, Stambaugh, Yu, and Yuan 2015, and Stambaugh and Yuan 2016).

4.1 Portfolio Formation

The portfolio sorting approach is conducted based on daily, weekly, and monthly frequencies respectively. The weekly panel and monthly panel is constructed based on daily dataset. In particular, I (1) aggregate (sum) Wednesday-to-Wednesday protection returns from daily data and average out the CPE accordingly; (2) aggregate (sum) monthly protection returns from daily and average out the CPE accordingly. To form portfolios, at each period t, I sort 5-year CDS contracts into five (both equal-weighted and value-weighted) quintile portfolios using CPE (form the smallest to the biggest). Next, I track the subsequent period protection returns. The portfolios are rebalanced at the end of each period. The sample period is from Jan 2001 to Dec 2015. Table 3 reports the result.

[**Table 3 & Figure 1 about here**]

4.2 Results

Table 3 presents the average raw returns of both equal-weighted and value-weighted CPE quintile portfolios across CPE1, CPE2, and CPE3 respectively. As reported in Panel A, the average protection returns of the equally weighted quintile portfolios sorted by the past CPE decline monotonically across the all three models at daily frequency (see Figure 1). A spread portfolio by longing CDSs in the smallest CPE quintile and shorting CDSs in the largest CPE quintile generates daily returns of 0.44% (NW t-stat = 14.4), 0.39% (NW t-stat = 13.6), and 0.39% (NW t-stat = 14.0) with respect to CPE1, CPE2, and CPE3. The significance of the mean of spread portfolios does not disappear as we move to weekly and even monthly frequency and the results are robust when I repeat the analysis using value-weighted scheme (see Panel B of Table 3). This empirical finding strongly suggests sluggishly adjustments of CDS prices respect to CPE - overpriced CDS at time t will tend to reverse downwards from t to t+1 while returns of underpriced CDS at time t will reverse upwards from t to t+1.

The average protection returns of CPE sorted portfolio exhibit an asymmetric pattern. The magnitudes of reversals in the smallest CPE quintile are larger than that (in terms of absolute magnitude) in the largest CPE portfolio quintile. For example, at daily frequency, the average returns of small CPE quintile are about 0.25%, 0.33%, and 0.33%, which are way larger than the average returns of the large CPE quintile: about negative 0.10%, 0.03%, and 0.03% respect to CPE1, CPE2, and CPE3. This also holds for all other frequencies and value-weighted case. It seems that investors tend to overreact to past undervalued CDS spreads. I investigate this in the Section 5.2.

To test whether profits of investment strategies are decreasing as the explanation power increases. I redo the cross-sectional estimation of pricing errors by considering market leverage as a single factor to explain CDS spreads and compute the pricing errors based on this model. I next include each additional explanatory variable on top of the single factor model. The cross-sectional regression is specified as

$$\text{Ln CDS}_{i,t} = \alpha_t + X_{i,t}\gamma_t + e_{i,t}$$

The layout of selection of X is following:

$$
\mathrm{X} = \begin{cases}
\text{Specification 1. Market Leverage} \\
\text{Specification 2. Market Leverage, Volatility} \\
\text{Specification 3. Market Leverage, Volatility, M/B} \\
\text{Specification 4. Market Leverage, Volatility, M/B, ROA} \\
\text{Specification 5. Market Leverage, Volatility, M/B, ROA, LogSize} \\
\text{Specification 6. Market Leverage, Volatility, M/B, ROA, LogSize, Cash} \\
\text{Specification 7. Market Leverage, Volatility, M/B, ROA, LogSize, Cash, Corporate Liquidity} \\
\text{Specification 8. Market Leverage, Volatility, M/B, ROA, LogSize, Cash, Corporate Liquidity, EPS}
\end{cases}
$$

[**Figure 2 about here**]

In Panel A of Figure 1, I plot average of long-short portfolio returns between the most undervalued CPE and the most overvalued CPE. In Panel B of Figure 1, I plot the time-series average of adjusted R^2 along specification 1 to specification 8 in X. As shown in specification 1, the cross-sectional CDS valuation model generates only 10% adjusted R^2 with considering Market leverage only. However, the adjusted R^2 jumps to about 28% when stock volatility is included (as in Specification 2 in X). As for the average of long-short portfolio returns, I find that it increases from 0.15% per day to 0.30% per day.

Another small jump in R^2 is from specification 4 to specification 5 when market size is included. However, it appears that there is no effect on the spread portfolio returns from specification 4 to 5. The average portfolio returns is flat from specification 2 to 8.

Taken together, the evidence is against the common sense that performance of spread portfolio should reduce when more explanatory variables are included. The most influential factor, volatility, is even improving the performance rather than the other ways around. It may suggest the average R^2 is not a good indicator to look at and other powerful test statistics need to be introduced.

4.3 Alternative Measure of CPE

To ensure the pricing errors convey different information from the CDS spread level, I conduct an alternative measure of CPE by standardizing CPE by the CDS spread level:

$$\text{Alternative CPEj}_{i,t} = \frac{\text{CPEj}_{i,t}}{\text{CDS Spread}_{i,t}} \tag{5}$$

where j=1,2,3; i indicates firm and t indicates day. I repeat the analysis of Table 3 by using alternative CPE. Table 4 reports the results.

[**Table 4 about here**]

In table 4, I find that the performance of CPE portfolios become stronger when I control for CDS spread. For example, the spread portfolio of alternative CPE panels are about 3bps-8bps stronger than these reported in Table 3. This makes sure that CPE conveying independent information to CDS spread level.

5 Economic Interpretation

The focus in this section is on testing whether information contents in CPEs are related to mispricing or not.

5.1 CDS Liquidity

CDS contracts are more liquid than bonds. Longstaff et al. (2005), Longsta, Mithal, and Neis (2005) consider CDS spreads as a pure measure of default risk without affected by liquidity. Recent empirical evidence, however, show that CDS spreads are not the pure default premium (Tang and Yan (2007), Bongaerts, de Jong, and Driessen (2011), Chen, Fabozzi, and Sverdlove (2010), Buhler and Trapp (2010)). It suggests a overvalued default spread if CDS spreads carry a liquidity premium. I conjecture that CDS illiquidity is an important factor influencing the predictive power of CPE. I expect that average returns of spread portfolio decline as CDS liquidity improving.

I consider two measures for CDS illiquidity. The first measure is CDS market depth, which is based on the number of contributors that provide quotes to Markit on any given date. The higher the number of contributors, the better should be the CDS liquidity. Gala, Qiu, and Yu (2010) and Kapadia and Pu (2012) use this as measurement of CDS liquidity. The second measure is zerospread, which is the proportion of zero CDS prices changes over total number of non-zero CDS prices over the past 30 days. The lower the zerospread, the better should be the CDS liquidity.

At the end of each day, I form 4×4 portfolios with an independent double sort CPE and CDS illiquidity measure. This results 16 portfolios, which are equally-weighted held for subsequent days. Table 5 reports the results.

[**Table 5 about here**]

Panel A of Table 5 reports the result of an independent double sort of CPE and CDS depth. Each entry of this table reports the *average long-short portfolio returns* at day t between the smallest CPE and the highest CPE at day t-1. The results indicate that the average returns of spread portfolio in poor CDS depth quartile are significantly larger than those reported in the quartile with good liquidity quartile. Take equal-weighted case as an example (left panel), in the most illiquid CDS quartile (Low quartile) with the smallest number of contributors, the long-short portfolio (between the smallest CPE and the highest CPE) generates the highest returns about 0.45% per day with NW t-stat=8.2, 0.47% per day with NW t-stat=11.1, and 0.46% per day with NW t-stat=11.2 for CPE1, CPE2, and CPE3. These numbers are significantly larger than the good liquidity quartile with 0.07% per day with NW t-stat=2.5, 0.17% per day with NW t-stat=6.9, and 0.17% per day with NW t-stat=6.6. Taking the long-short portfolio between the 4th CDS depth quartile and the 1st CDS depth quartile yield a significantly negative return - the "L-H" is 0.39% per day with NW t-stat=6.8, 0.3% per day with NW t-stat=6.6, and 0.3% per day with NW t-stat=6.6. The evidence suggests that a significant amount of variations in CPEs portfolio returns can be explained by CDS liquidity proxied by CDS depth. Panel B of Table 5 reports the result of an independent double sort of CPE and Zerospread showing the similar findings compared with Panel A: CDSs with poor liquidity earns higher CPE spread returns, whereas CDSs with good liquidity earns relatively lower CPE spread returns.

In summary, the empirical evidence shows that CDS liquidity should serve as a significant factor that explains the large amount of the variations in the performance of CPE strategies. This suggests that CDS spreads carry a liquidity premium.

5.2 Macro Uncertainty

Macro-uncertainty should affect CDS prices via influencing investors' perceptions given valuation. Ambiguity-averse investors should react more strongly to bad news than to good news given high level of uncertainty (Epstein and Schneider (2008)). As a result, it makes economic sense to put more weights on the low continuation values during the time of high uncertainty period. During periods with high uncertainty, when observed realized credit spreads are valued lower than the expectation or say CPE<0, it may trigger credit buyers to demand more credit protection in presence of ambiguity utilities. Thus, I expect that CPE reversal phenomenon is more pronounced during high uncertainty period due to overreaction among the long leg or lag with the undervalued, smallest CPE.

To proxy for macro uncertainty, I use VIX, EPU, and CFSI (credit sector). I split the CPE sorted portfolio by the median of VIX, EPU, and CFSI (credit sector) respectively. The results are reported in Table 6.

[Table 6 about here]

Using VIX as proxy for macro uncertainty and splitting the sample into high uncertainty regime and low uncertainty regime by median of daily VIX from 2001 to 2015 in Panel A, I find that indeed, in the high uncertainty regime, the most undervalued of CPE strategy generates greater returns compared with low VIX regime. Specifically, For high VIX regime, the average returns of the most undervalue leg is about 0.47%, 0.55%, 0.55% respect to CPE1, CPE2, and CPE3 that is way greater than these reported in the undervalue leg of low VIX regime with 0.04%, 0.11%, and 0.12% for CPE1, CPE2, and CPE3 respectively. Furthermore, the spread portfolio between the most undervalued quintile and the most overvalued quintile for high VIX regime is 0.5%, 0.48%, and 0.48% per day, which are about two times larger than that of low VIX regime: 0.22%, 0.24%, and 0.24%.

Panel B and Panel C report the similar results by replacing VIX to CFSI and EPU respectively. Although these deliver a consistent message as to Panel A, the performances are not as strong as the VIX case.

6 Credit Default Swaps Price Errors Spillover

In this section, I investigate whether and how pricing errors of CDS spillover to other capital markets such as stock, corporate bond, and options issued by the same firm, with the focus on firm-specific information.

Since capital markets are segmented and populated by different types of traders with different information sets and motivations, trading activities [15] across various markets or trading venues are complex and hard to pin down by efficiency market hypothesis alone. Nevertheless, by focusing on market consequences (e.g., price reaction of one market respect to the other) may provide insights on understanding the complex interactions across capital markets. For instance, liquidity is one of the key channel to understand the links . The model of multi-market trading developed by Easley, O'Hara, and Srinivas (1998) suggested that, given a common fundamental component shared by different securities, informed traders prefer to use the most liquid capital market to process private information. As such, causing earlier price discovery of one market relative to the other. A leading empirical support is provided by Hilscher, Pollet, and Wilson (2015) who found that stock markets are, in general, more informed than CDS markets. Different opinions (w.r.t. different traders treat the same firm specific information differently among different capital markets) is also an important factor to understand the links. Goldstein, Li, and Yang (2013) pointed out that different opinions should generate various directions of trades (e.g., hedgers and speculators are likely to place opposite orders given the same information) thus reduce the overall price informativeness.

Price imperfection of one market should not imply the price imperfection of other markets if capital markets are completely independent. This hypothesis is likely to be rejected in real world as Yu (2005) and Kapadia and Pu (2012) who have already pointed out that investors do trade on one market relying on other market's information. The rejection of the hypothesis delivers new

[15] e.g., involving informed strategies, speculative trades, and hedging, etc.

insights on the complex inter-capital markets trading activities. Thus understanding this through getting a clearer view on following questions like (1) whether one market will make mistakes given the observed mistakes by the other market; (2) how long do those mistakes be corrected; should deliver a new and simple way to look at the complex interactions among capital markets.

6.1 CPE & Asset returns

6.1.1 Prepare for Corporate Bonds and Options data. Corporate bonds data are collected from TRACE covering July 2002 to Dec 2015. I clean TRACE dataset following Dick-Nielsen (2014)'s way [16] mainly considering three steps: (1) clean same-day corrections and cancellations, (2) remove reversals and the matching original transaction report, and (3) delete agency/principal transactions double counting[17]. I compute the bond return at individual bond level by

$$\text{Bond Return}_{i,j,t} = P_{i,j,t}/P_{i,j,t-1} - 1$$

where i is firm, j is bond, and t is day. I then aggregate[18] bond returns regard to each firm at each day and link them to the CDS/stock merge dataset using first 6 digit CUSIP. In particular, I conduct equal-weighted scheme to aggregate individual bond level data to firm level data. The options data are collected from Option Metrics IvyDB database. The sample period is from Jan 2001 to Dec 2015. I apply couple of filters to reduce the data errors. First, I remove the observations that break the arbitrage bounds[19]. Second, I remove the case where bid price is larger than the ask price. Third, I require that the bid-ask spread is higher than the minimum tick size, which is equal to \$0.05 when the option price is below \$3, and \$0.10 when the option price is higher than \$3. Fourth, to ensure liquidity, I remove all observations with zero open interest. Fifth, I consider nearly at-the-money and out-of-money options only. [20]. At each contract level, I compute return

[16] Dick-Nielsen (2009) reported that 7.7% of all reports in TRACE are errors and in some cases up to 18% of the reports should be deleted

[17] Please refer to Dick-Nielsen (2014) for more detail discussion. Dick-Nielsen attached a SAS code to do the job in the discussion paper.

[18] I admit that lack of information on bond characteristics such as maturity dates can be a limitation of the matching (These information is provided by Mergent Fixed Income Securities (FISD) Database but I do not have subscription).

[19] American call options lower bounds C>=S-K, upper bound: C<=S. American put options lower bounds: P<=K, upper bound: P>= max(0,K-S), where K is strike price, S is stock price without dividends, C is call price and P is put price. I focus on American options only.

[20] see Driessen, Maenhout,and Vilkov(2009), Goyal and Saretto (2009) for more detail discussion on the data cleaning process.

by

$$\text{Options Return}_{i,j,t} = P_{i,j,t}/P_{i,j,t-1} - 1$$

where i is firm, j is option contracts, and t is day, option prices $P_{i,j,t}$ is computed as $\frac{\text{closing ask+closing bid}}{2}$.

6.1.2 Do CPE Predict Stock Returns. I first investigate whether CPE can predict cross-sectional stock market returns. CPEs should not affect stock returns at all if stock markets figure out that the CDS price movements are just pricing errors. Alternatively, the spillover effect from CPEs to stock returns suggests that stock markets do not immediately realize that the CDS price reactions are in fact price errors. As such, the stock markets should move conditional on the transitory CDS price changes caused by future CPE corrections.

I test the two hypotheses using portfolio sorting approach. To form portfolios, at each period t+1, I sort stock returns into five (both equal-weighted and value-weighted) quintile portfolios using their lagged CPE (form the smallest to the biggest). The long-short portfolio between the highest CPE and the lowest CPE is reported in column H-L. Table 7 contains the results. The sorting approach is conducted based on daily, weekly, and monthly frequencies respectively.

[Table 7 about here]

Results There are clear increasing patterns of average return respect to three CPE quintile at daily and weekly frequency implying a strong positive relation between CPE and subsequent stock returns. The average daily returns of long-short strategy or "H-L" between the highest CPE quintile and the lowest CPE quintile are statistically significant for CPE2 2&3 of equal-weighted cases and for all of value-weighted cases at both daily and weekly frequency. The statistically insignificant result of "H-L" for CPE 1 at daily frequency for the equal-weighted case suggests that arbitrageurs are more likely to trade large firms given realized CPE (since this is highly significant for the value-weighted case at daily frequency).

Interpretation This result is consistent with insight of contingent claim analysis - changes of equity price are increasing respect to fundamental value of firm as it mimic the call options payoff, whereas changes of CDS prices are decreasing respect to fundamental value of firm as it mimic the put options payoffs, the sensitivities between CDS price changes and stock price changes should expected to be negative. If arbitrageurs trade on CPE, it should push the mispriced CDS spreads to the fundamental level, but at the same time, it produces negative shocks to stocks by encouraging more stock selling pressure. As a result, within a same reference entity, stock returns will raise (decline) given overvalued (undervalued) CDS at t. This empirical evidence lends a great support to capital structure arbitrage literature (Yu 2005; Kapadia and Pu 2012 among many others).

This predictive result is also related to studies on the link between CDS and equity markets by considering the informational content from CDS markets to equity markets. For example, Han, Subrahmanyam, and Zhou (2017) showed that credit slope negatively predicts next-month cross-section stock returns. By estimating firm-specific measures of credit risk premia from the CDS forward curve following the ideas of Cochrane and Piazzesi (2005), Friewald, Wagner, and Zechner (2014) found that estimated risk positively drives equity excess returns. This study provides the related evidence that CPE positively relates to future cross-sectional stock returns.

How Long Does the Predictability Reverse? Stock markets should stop to ride on CDS market mispricing or even trade oppositely (buy stocks with the most undervalued CDS and sell stocks with the most overvalued CDS) to correct the mistake when they understand the short-run CDS price changes are in fact due to price errors rather than changes in fundamentals. Thus, the payoff of long-short portfolios between stocks with the highest CPE and stocks with the lowest CPE should reverse in future[21].

I form 30 portfolios to test this idea. I compute Fama-French 5 factor alphas of "H-L" at day t using CPE information at t-1, t-2, t-3, ..., t-30 respectively. The "H-L" stands for a long-short strategies on stock returns between the highest CPE quintile and the lowest CPE quintile. I plot

[21] I form a simple example to better understand this idea. Suppose the current observed CDS price is 100bps but the true CDS price is 120bps and the current stock price is $10. Ceteris paribus, CDS price should increase to match the true price. If stock traders know the true CDS price is 120 bps, then they will not trade on the stock no matter what the current CDS price is. Otherwise, if they think 100bps is the fair price (actually is not), then they will sell stocks when the CDS price move from 100bps towards 120bps. As a result, it pushes down the stock price to say $8. The selling behavior should, however, stop and reverse when stock traders learn that CDS price changes (from 100bps to 120bps) are pricing errors - implying that the initial stock is fairly priced and the current stock price is undervalued (stock price should be $10 for all time). Traders should buy back their shares to push the stock prices back to $10.

the time-series average of alphas (from t-1 to t-30) respect to CPE1, CPE2, and CPE3 in Figure 3 and I plot the t-statistics of those alphas (from t-1 to t-30) respect to CPE1, CPE2, and CPE3 in Figure 4.

[**Figure 3 & 4 about here**]

From Figure 3, we see that the alpha of "H-L" strategy (buy bundle of stocks with the highest CPEs at t and sell bundle of stocks with low CPEs at t-k for k=1,2,...,30.) is increasing up to 15 and decreasing gradually afterwards. From Figure 4, we see that there is a clear decreasing pattern for t-statistics for three CPE1, CPE2, and CPE3. The reversal happens after 15 days - namely the absolute t-statistics of three alphas are increasing and reach the 1% significant level (peaked) at t=27 and then reduce sharply to zero since then. This is a clear evidence of reversal.

In summary, the evidence suggests that stock markets indeed at first do not realize the CDS pricing errors. They continue ride on the CDS price reactions caused by pricing errors for about 15 days. However, stock markets start to aware this and reversely (significantly) react to correct the mistake they made about CPEs. It takes another 15 days. This part delivers the message that these trading behaviors are not social optimal. It consistent with Goldstein, Li, and Yang (2013) who pointed out that the complex trading interaction among different capital markets will sometimes reduce the overall price informativeness.

6.1.3 Do CPE Predict Bond Returns. To see whether CPEs can predict corporate bond returns, I conduct a portfolio sorting analysis between future bond returns and past CPEs similar to Table 7. On the one hand, CPEs are more likely to predict corporate bond returns due to the tight information connection between CDS and bond markets. For example, the increase of CDS spread of undervalued CDS signal the increase of expected yield thus lower the future bond price vice versa. On the other hand, the CPEs may not predict corporate bond returns if corporate bond markets understand that CDS price changes are due to pricing errors.

[**Table 8 about here**]

Results Interestingly, in Table 8, I find that CPEs deliver weak predictive power on cross-sectional corporate bond returns. The "H-L" portfolio are in general statistically indifferent from zero among all frequencies for equal-weighted case (Panel A) and value-weighted case (Panel B).

Interpretation The result shows no predictability of CPE towards corporate bond markets. It seems to suggest that corporate bond markets understand CDS market pricing errors. There are two reasons to believe the result. Firstly, the market for the U.S. corporate bonds is dominated by institutional investors who suppose to have better understanding on the value of outstanding corporate debts, thus they are more likely to detect whether the current CDS prices are inflated or deflated relative to underlying bonds. Secondly, there may exist a set of speculators who bet on CDS mispricing and selectively proceed the above information in a more capital liquid market. Both stocks and options markets are supposed to be better trading venues (stock markets are more liquid, and options markets allow informed investors to hide their private information) compared with corporate bond markets.

6.1.4 Do CPE Predict Returns of Puts & Calls.

Like the idea discussed in stock and corporate bond markets case, options markets may be predicted by CPE if CPEs are not immediately identified as errors and the link between the two markets is tight, otherwise option markets should not react to CPE. Additionally, the options market may favor with arbitrageurs because of their special designs such as allowing leverage, no short-sale constraints, and many contracts allowing them to hide information compared with stock markets. Thus I test whether CPEs carry information on future stock returns. I conduct a panel regression rather a portfolio sorting to test the predictability of CPEs on options returns because of the complex price structure of options dataset - there are different conditions (e.g., time-to-maturities, strike price, underlying spot price, and liquidity etc.) to drive the option prices. Thus this is hard to control all of them by using solely portfolio sorting approach. The regression specification is:

$$\begin{aligned} \mathrm{R}_{i,j,t+1} &= \alpha + \beta_1 \mathrm{CPE}_{j,t}/10000 + \beta_2 \mathrm{TTM}_{i,j,t} + \beta_3 \mathrm{Moneyness}_{i,j,t} + \beta_4 \mathrm{Strike} + \beta_5 \mathrm{Implied\_Vola}_{i,j,t-1} \\ &+ \beta_6 \mathrm{BA\_spread}_{i,j,t-1} + \beta_7 \mathrm{Open\_Interest}_{i,j,t-1} + g_j + \epsilon_{i,j,t+1} \end{aligned} \tag{6}$$

where i is option contracts, j is firm, and t is date. TTM is time-to-maturity for each option contract, Moneyness is ratio of strike over spot price, Strike is strike price of options contract, implied Vola is option implied volatility, BA spread is 0.5*(bid price+offer price), g_j indicates the option contract fixed effect dummies. The standard errors for the specification are clustered by date, CPE includes CPE1, CPE2, and CPE3, and R includes call options returns and put options returns respectively. Table 9 reports the result of put options case and Table 10 reports the result of call options case.

[**Table 9 & 10 about here**]

Results Table 9 reports the predictability result of CPEs on future put option returns. Column (1) - (3) report the estimation result by including CPE1, CPE2, and CPE3 without including control variables. The results show that the point estimate of the three models are all negative and statistically significant. Column (4) - (6), I conduct the panel regression estimation by adding control variables such as time-to-maturity, moneyness, open interests, strike price, implied volatilities. The controls like time-to-maturity, moneyness are at the same period compared with the option returns since those characteristics are directly linking to option prices based on option pricing models. The controls like open interest, lagged option prices, and implied volatility are at day t-1, which is not the direct input of option pricing model but are very important factors affecting option price dynamics. The point estimates of the three models remain to be negative and statistical significant. The evidence suggests that CPE do contain valuable information that affect the future put options returns. For the case of call option reported in Table 10, I find that CPE cannot predict future call options returns.

Interpretation Table 9 & 10 indicate that CPE can predict put options returns, whereas cannot predict call options returns. The negative predictive powers of CPE are consistent with the view that put options markets ride on CDS market mispricing. Specifically, since high CPEs predicts a low CDS future returns, which are supposed to indicate a low returns of put options (CDS returns are supposed to be positively comove with put options return dynamics since they can be considered as substitutions). In terms of the part that CPEs cannot predict call options returns suggests the less important link between CDS and call options. Namely, it is naturally to expect that arbitrageurs shift to put options rather call options given CDS markets news. However, to decide the choose between put options and stock markets is difficult and more beyond the boundary of liquidity. One needs to understand trade motivations, which turn out to be an empirical question.

6.2 CPE & Leverage effect

Next, I examine whether CPE can predict stock market volatilities. This exercise has important implication on the leverage effect hypothesis by Black (1976): when stock prices fall, companies become more levered since the relative value of their debt rises. As a result, their stock becomes more risker thereby drive up the future volatility. This hypothesis is argued by its reverse causality because an anticipated rise in volatility requires higher rate of return thus leads to a reduce in current stock return (Figlewski and Wang (2000), French et al., (1987), Campbell and Hentschel (1992), Hasanhodzic and Lo (2011)). The empirical challenge is that stock returns are, by construction, endogenous to stock volatility.

I argue that CPE can be considered as a direct treatment to separate leverage effect hypothesis from volatility feedback hypothesis without directly using information on stock returns. The reason is following: based on the strong predictability of CPE reversal documented in Table 3, undervalued CDS should predict future higher CDS spreads and overvalued CDS should predict future lower CDS spreads. Since market value of corporate debt should positive associate with CDS spread, increasing (decreasing) CDS spread should increase (decrease) the capital structure of firms. Since the debt holders' claim on firm value is limited to face value of the bonds, so a significant amount of variations in total firm value will be transmitted to the equity affecting future volatility of stock returns. Built upon this insight, I predict that change of CPE negatively predict future change of volatility.

In terms of deriving daily volatility, one technical issue is model risks incurred by various selections of volatility models. In order to mitigate this concern, I proxy daily realized volatility using intraday stock returns from TAQ database from 2001 to 2013. In particular, the intraday volatility is second-by-second trade based volatility of stock on day T. This is calculated as:

$$\sigma_{i,t}^2 = \frac{\sum_{t=1}^{T}(r_{i,t} - \bar{r}_{i,t})^2}{T-1} \tag{7}$$

The traded-based intraday log returns for each firm is computed as following way: on day t, the ith intraday return is given by

$$r_{t,i} = p_{t,i/N} - p_{t,(i-1)/N} \tag{8}$$

where p is the natural logarithm of the price (second-by-second) and N is the number of return observations in a trading day. I run the following regression:

$$\Delta\sigma_{i,t+1} = \alpha + \beta\Delta\text{CPE}_{i,t}/10000 + X_{i,t}\gamma + \delta_j + e_{i,t+1} \tag{9}$$

where i $\in$ [1,N] indicates firm, t indicates day. $X_{i,t}$ is N by K matrix includes control variables such as stock returns, dollar volume of stocks, and stock market liquidity proxed by effective spreads (K=3 in this case). γ is K by 1 vector. δ_j is firm fixed effect. The standard errors of this regression are clustered by date. Consistent with leverage effect literature, I use changes of volatility and change of CPE. Table 8 reports the result.

[Table 11 about here]

In table 11, I find that $\Delta\text{CPE}_{i,t}$ indeed negatively predicts future volatility shock. In particular, in column (1)-(3) without including control variables, slope coefficients are at -4.084 (t-stat=-4.57), -1.108 (t-stat=-3.81), and -1.026 (t-stat=-3.35) for CPE1, CPE2, and CPE3 respectively. Additionally, as shown in column (4)-(6), I find that the predictive power of CPE on future stock volatility cannot be completely explained by lagged stock volatility, lagged stock returns, lagged stock liquidity, and lagged stock trading volume.

In summary, the results of predicting change of future volatility contributes to the existing debate on leverage effect. I suggest that CPE may serve as a good instrument to identify the leverage effect channel. Since CDS is direct information source on debt obligation of corporation, its impact on future stock volatility may serve as the direct treatment to separate leverage effect from volatility feedback hypothesis. Thus, it reaffirms the existence of Black (1976)'s leverage effect.

7 Conclusion

This article examines capital market consequences of CDS pricing errors. I find that CDS pricing errors not only has strong predictive power on CDS markets in daily, weekly, and monthly frequency, but also predict cross-sectional stock returns, puts returns and volatility. However, CPE does not exhibit predictive power on corporate bonds and call options.

This article conducts several implications. Firstly, it suggests capital markets sometime make mistakes, and such mistakes should reduce total price informativeness. Secondly, it casts doubt on high degree of explanation power of the existing CDS valuation models because of the huge profitability found by using CPE thus suggests a better framework to evaluate those models.

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Table 1. Summary statistics Table 1 reports the summary statistics of market variables and firm characteristics for 884 U.S. firms from Jan 2001 to Dec 2015, a total of 1,781,846 firm-day observations. Panel A reports the sample average of each variable on both the pooled sample and at each credit default swap quintile. Panel B reports cross-sectional standard deviations (XS STD) - time series averages of the cross-sectional standard deviation on each date; and time-series standard deviation (TS STD) - cross-sectional averages of the time-series standard deviation for each firm. CDS (bps) is 5-year CDS spread obtained from Markit. CDS return is percentage changes of CDS spreads. Market leverage is computed following Ericsson, Jacobs, and Oviedo (2009). Stock market volatility is computed using EWMA model following Ericsson, Jacobs, and Oviedo (2009). Stock price is market closing price from CRSP. EPS is earnings per share excluding extraordinary items. Cash holding is defined as cash and cash equivalent over market value of total assets. M/B ratio is market equity to book equity ratio. ROA is return on total asset. Net working capital is computed as ratio of working capital (WCAPQ, in balance sheet) and total asset. Market cap (in million) is market value of the equity of the firm defined as closing pricing times number of shares outstanding. Rating is credit rating obtained from Markit. T10 is 10-year Treasury Bond Yields which is a constant maturity index constructed by the U.S. Treasury based on the most actively traded issues in the 10-year maturity segment. VIX measures market expectation of near term volatility conveyed by stock index option prices. CFSI is The Cleveland Financial Stress Index obtained from FRED.

	Panel A: Mean at CDS Quintiles						Panel B: STDV	
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)
Characteristics	Pooled	Small	2	3	4	High	XS STD	TS STD
CDS (bps)	167.50	34.414	59.666	91.661	158.651	492.983	228.681	115.834
CDS return	0.11%	-0.06%	0.05%	0.13%	0.14%	0.27%	0.041	0.029
Market leverage	0.371	0.249	0.320	0.368	0.415	0.502	0.306	0.063
Stock volatility	0.018	0.013	0.015	0.016	0.018	0.025	0.009	0.011
Stock price	263.829	313.692	482.803	339.532	158.052	25.143	4485.710	61.688
Stock return	0.047%	0.043%	0.045%	0.047%	0.050%	0.051%	0.019	0.024
EPS	11.50	17.581	18.040	15.188	6.316	0.401	159.395	4.611
Cash holding	7.38%	5.27%	6.64%	7.24%	7.90%	9.84%	0.101	0.019
M/B ratio	16.07	44.218	15.032	9.738	6.883	4.498	67.505	6.284
ROA	0.497%	0.301%	0.597%	0.676%	0.650%	0.258%	0.025	0.006
Net Working capital	8.361%	5.077%	6.595%	7.319%	8.270%	14.542%	0.245	0.035
Market cap (Million)	19819	48894	21712	14571	9097	4827	40257	5019
Rating	4.048	3.144	3.679	3.943	4.326	5.146	1.102	0.035
T10y	3.46	-	-	-	-	-	-	0.762
VIX	20.05	-	-	-	-	-	-	8.180
EPU	107.37	-	-	-	-	-	-	72.02
CFSI	10.29	-	-	-	-	-	-	2.110
S&P 500 level	1347.45	-	-	-	-	-	-	250.935
S&P 500 return	0.02%	-	-	-	-	-	-	0.012

Table 2. Summary measures of CPE This table reports the summary statistics of three empirical CDS valuation models introduced in Section 3. In particular, model 1 is time-series regression model based on Eqs.(1). Model 2 & 3 are cross-sectional regression model based on Eqs.(2), where Model 2 considers two factors such as market leverage and stock volatility; model 3 includes two factors model as well as firm fundamental variables such as EPS, Cash, M/B, ROA, Market size, Corporate liquidity. Panel A reports the summary statistics of adjusted R^2. Avg. indicates pooled sample average of all observations. Stdv. indicates pooled sample standard deviations. 25p. is 25 percentile, 50p. is 50 percentile, and 75p. is 75 percentile. In panel B, I report the sample mean (standard deviations are reported in the brackets) at each credit default swap quintile.

Panel A	Avg.	Stdv.	25p.	50p.	75p.
Model 1	58.24%	21.54%	43.95%	62.53%	74.64%
Model 2	29.71%	7.55%	23.84%	29.18%	35.82%
Model 3	36.12%	5.70%	32.03%	36.02%	40.32%

Panel B	Small CDS	2	3	4	High CDS
CPE 1	-3.924	-4.037	-1.077	7.112	35.889
	(15.18)	(24.91)	(53.65)	(95.53)	(428.12)
CPE 2	-42.111	-31.493	-13.155	31.552	268.003
	(43.51)	(50.95)	(71.58)	(116.87)	(396.55)
CPE 3	-38.391	-32.420	-15.025	28.746	267.529
	(45.48)	(50.28)	(69.11)	(110.77)	(397.82)

Table 3. Do CPE predict future CDS price changes? This table reports the single-sorting portfolio analysis results on *CDS returns* using lagged CPE. The portfolio sorting approach is conducted for daily, weekly, and monthly frequencies. Equal-weight and value-weight are employed in Panel A and B respectively. To form portfolios, at each period t, I sort 5-year *CDS returns* into five quintile portfolios using CPE at period t-1 (form the smallest to the biggest). The portfolios are then rebalanced at each period t. "S-L" indicates the mean of spread portfolios returns of CDS between the smallest CPE quintile and the largest CPE quintile. Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	Panel A: equal weighted panel						**Panel B: value weighted panel**					
	Small CPE	2	3	4	Large CPE	S-L	Small CPE	2	3	4	Large CPE	S-L
Daily												
CPE1	0.25%	0.18%	0.09%	-0.01%	-0.10%	0.36%	0.28%	0.22%	0.08%	-0.02%	-0.15%	0.42%
	(5.7)	(4.5)	(2.5)	-(0.2)	-(2.5)	(13.2)	(4.2)	(4.3)	(1.8)	-(0.4)	-(3.1)	(8.9)
CPE2	0.33%	0.14%	0.06%	-0.01%	-0.03%	0.36%	0.37%	0.09%	-0.01%	-0.08%	-0.06%	0.44%
	(7.4)	(3.7)	(1.6)	-(0.3)	-(0.8)	(12.9)	(5.9)	(2.1)	-(0.1)	-(1.7)	-(1.4)	(8.2)
CPE3	0.33%	0.13%	0.06%	-0.01%	-0.03%	0.36%	0.34%	0.16%	0.08%	-0.04%	-0.06%	0.40%
	(7.5)	(3.6)	(1.5)	-(0.2)	-(0.8)	(13.3)	(6.9)	(3.9)	(1.9)	-(0.8)	-(1.3)	(9.9)
Weekly												
CPE 1	0.57%	0.47%	0.31%	0.11%	-0.08%	0.64%	0.75%	0.64%	0.27%	0.08%	-0.19%	0.94%
	(2.1)	(2.1)	(1.4)	(0.5)	-(0.3)	(5.0)	(2.2)	(2.2)	(1.1)	(0.3)	-(0.7)	(4.4)
CPE 2	1.00%	0.39%	0.20%	-0.06%	-0.03%	1.04%	1.21%	0.28%	0.03%	-0.25%	-0.04%	1.25%
	(3.9)	(1.7)	(1.0)	-(0.3)	-(0.2)	(7.9)	(3.8)	(1.0)	(0.1)	-(1.0)	-(0.2)	(5.0)
CPE 3	0.99%	0.41%	0.17%	-0.04%	-0.03%	1.02%	1.13%	0.48%	0.25%	-0.07%	-0.06%	1.19%
	(4.0)	(1.9)	(0.8)	-(0.2)	-(0.1)	(8.4)	(4.1)	(2.1)	(1.0)	-(0.3)	-(0.2)	(6.1)
Month												
CPE 1	2.09%	1.67%	1.41%	0.75%	0.25%	1.83%	2.80%	2.17%	1.42%	0.70%	-0.20%	3.00%
	(1.3)	(1.3)	(1.1)	(0.7)	(0.2)	(2.3)	(1.4)	(1.1)	(1.0)	(0.5)	-(0.2)	(2.6)
CPE 2	4.02%	1.72%	0.80%	0.08%	0.14%	3.87%	4.73%	1.58%	0.39%	-0.39%	0.19%	4.53%
	(2.6)	(1.3)	(0.8)	(0.1)	(0.1)	(4.7)	(2.5)	(1.0)	(0.3)	-(0.3)	(0.2)	(3.4)
CPE 3	3.89%	1.76%	0.81%	0.21%	0.09%	3.80%	4.89%	2.10%	1.33%	0.49%	0.11%	4.78%
	(2.6)	(1.5)	(0.7)	(0.2)	(0.1)	(4.8)	(2.9)	(1.5)	(0.9)	(0.3)	(0.1)	(4.0)

Table 4. Do CPE predict future CDS price changes? - Alternative CPE. This table reports the single-sorting portfolio analysis results on *CDS returns* using (lagged) an alternative measure of CPE is by standardizing CPE using the CDS spread level: Alternative CPEj$_{i,t}$ = $\frac{\text{CPEj}_{i,t}}{\text{CDS Spread}_{i,t}}$, where j=1,2,3; i indicates firm and t can be represented as day, week, or month. The portfolio sorting approach is conducted for daily, weekly, and monthly frequencies. Equal-weight and value-weight are employed in Panel A and B respectively. To form portfolios, at each period t, I sort 5-year *CDS returns* (at period t) into five quintile portfolios using CPE at period t-1 (form the smallest to the biggest). The portfolios are then rebalanced at each period t. "S-L" indicates the mean of spread portfolios returns of CDS between the smallest CPE quintile and the largest CPE quintile. Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	Panel A: equal weighted panel						**Panel B: value weighted panel**					
	Small CPE	2	3	4	Large CPE	S-L	Small CPE	2	3	4	Large CPE	S-L
Daily												
CPE 1	0.34%	0.14%	0.05%	0.00%	-0.10%	0.44%	0.40%	0.15%	0.02%	-0.01%	-0.10%	0.50%
	(7.6)	(3.9)	(1.3)	-(0.1)	-(2.3)	(14.4)	(6.5)	(2.9)	(0.5)	-(0.3)	-(2.1)	(11.5)
CPE 2	0.33%	0.13%	0.08%	0.01%	-0.06%	0.39%	0.28%	0.06%	0.01%	-0.06%	-0.10%	0.38%
	(7.6)	(3.3)	(2.1)	(0.3)	-(1.8)	(13.6)	(5.2)	(1.3)	(0.3)	-(1.3)	-(2.4)	(8.5)
CPE 3	0.33%	0.13%	0.07%	0.01%	-0.06%	0.39%	0.35%	0.12%	0.05%	0.00%	-0.05%	0.40%
	(7.9)	(3.4)	(2.0)	(0.3)	-(1.7)	(14.0)	(6.3)	(2.9)	(1.0)	(0.1)	-(1.0)	(8.4)
Weekly												
CPE 1	0.75%	0.34%	0.22%	0.12%	-0.06%	0.81%	0.98%	0.46%	0.16%	0.09%	-0.02%	1.01%
	(2.8)	(1.7)	(1.0)	(0.5)	-(0.2)	(6.0)	(3.0)	(1.7)	(0.6)	(0.3)	-(0.1)	(5.1)
CPE 2	0.98%	0.39%	0.26%	0.05%	-0.18%	1.16%	0.84%	0.24%	0.10%	-0.13%	-0.30%	1.14%
	(3.8)	(1.8)	(1.2)	(0.2)	-(0.9)	(7.5)	(2.9)	(1.0)	(0.4)	-(0.5)	-(1.4)	(5.3)
CPE 3	0.96%	0.42%	0.23%	0.06%	-0.18%	1.14%	1.02%	0.41%	0.19%	0.07%	-0.11%	1.13%
	(3.9)	(2.0)	(1.1)	(0.3)	-(0.9)	(8.0)	(3.5)	(1.8)	(0.7)	(0.3)	-(0.4)	(5.2)
Month												
CPE1	2.75%	1.21%	0.97%	0.81%	0.44%	2.31%	3.67%	1.76%	1.02%	0.65%	0.55%	3.13%
	(1.7)	(1.0)	(0.8)	(0.7)	(0.4)	(2.8)	(1.7)	(1.1)	(0.7)	(0.5)	(0.4)	(2.6)
CPE2	3.85%	1.75%	1.17%	0.30%	-0.31%	4.16%	3.55%	1.31%	0.79%	-0.07%	-0.52%	4.07%
	(2.4)	(1.4)	(1.1)	(0.3)	-(0.3)	(4.2)	(1.9)	(0.9)	(0.6)	-(0.1)	-(0.5)	(3.1)
CPE3	3.69%	1.80%	1.18%	0.38%	-0.29%	3.98%	4.25%	1.79%	1.22%	0.84%	0.01%	4.24%
	(2.4)	(1.5)	(1.0)	(0.3)	-(0.3)	(4.4)	(2.2)	(1.3)	(0.9)	(0.6)	(0.0)	(4.7)

Table 5. CDS Liquidity and CPE profits. This table reports the double sort results of lagged CPE and CDS liquidity. I consider two measurements for CDS illiquidity. The first is CDS market depth, which is based on the number of contributors that provide quotes to Markit on any given date. The higher the number of contributors, the better should be the CDS liquidity. The second measure is zerospread, which is the proportion of zero CDS prices changes over total number of non-zero CDS prices over the past 30 days. The lower the zerospread, the better should be the CDS liquidity. I form 4 × 4 portfolios with an independent double sort of lagged CPE and CDS illiquidity measure. In particular, at the end of each day, CDS returns are sorted by lagged (1-day) CDS illiquidity into 4 groups, within each of group, I futher sort 5-year CDS returns by four groups based on lagged (1-day) CPE. Equal-weighted and value-weighted case are reported in left and right panel respectively. Panel A reports the case of CDS depth. Panel B reports the case of Zerospread. In panel A, "L-H" indicates the mean difference between low CDS depth quartile (proxy for bad liquidity) and high CDS depth quartile (proxy for good liquidity). In Panel B, "H-L" indicates the mean difference between high Zerospread quartile (proxy for bad liquidity) and low Zerospread quartile (proxy for good liquidity). Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	Left panel: equal weighted panel					**Right panel: value weighted panel**				
Panel A: CDS depth	Bad Liquidity			Good Liquidity		Bad Liquidity			Good Liquidity	
	Low	2	3	High	L-H	Low	2	3	High	L-H
CPE 1	0.45%	0.13%	0.08%	0.07%	0.39%	0.48%	0.19%	0.12%	0.09%	0.39%
	(8.2)	(4.7)	(3.2)	(2.5)	(6.8)	(6.3)	(4.3)	(3.8)	(2.8)	(5.1)
CPE 2	0.47%	0.19%	0.18%	0.17%	0.30%	0.68%	0.24%	0.18%	0.16%	0.53%
	(11.1)	(7.6)	(7.8)	(6.9)	(6.6)	(9.4)	(6.1)	(5.3)	(4.8)	(6.8)
CPE 3	0.46%	0.19%	0.18%	0.17%	0.30%	0.59%	0.22%	0.15%	0.18%	0.41%
	(11.2)	(8.4)	(7.8)	(7.6)	(6.6)	(8.3)	(5.9)	(4.4)	(5.8)	(5.5)
Panel B: Zerospread	Good Liquidity			Bad Liquidity		Bad Liquidity			Good Liquidity	
	Low	2	3	High	H-L	Low	2	3	High	H-L
CPE 1	0.03%	0.01%	0.13%	0.34%	0.31%	0.04%	-0.02%	0.17%	0.20%	0.16%
	(0.4)	(0.2)	(1.9)	(3.4)	(2.8)	(0.5)	-(0.3)	(1.6)	(1.6)	(1.2)
CPE 2	0.25%	0.24%	0.28%	0.43%	0.18%	0.21%	0.32%	0.44%	0.49%	0.28%
	(3.6)	(5.0)	(5.5)	(7.8)	(2.1)	(3.2)	(4.2)	(4.5)	(6.4)	(3.0)
CPE 3	0.26%	0.25%	0.27%	0.42%	0.17%	0.31%	0.27%	0.42%	0.44%	0.13%
	(3.9)	(5.2)	(5.4)	(7.3)	(1.8)	(3.3)	(3.8)	(4.7)	(5.4)	(1.0)

Table 6. High uncertainty regime versus low uncertainty regime. This table reports the portfolio single-sorting results by spliting the sample into the high uncertainty regime and the low uncertainty regime. To proxy for macro uncertainty, I use VIX, EPU, and CFSI (credit sector). I split the CPE sorted portfolio by the median level of VIX, EPU, and CFSI (credit sector). The median is computed based on entire data sample from Jan 2001 to Dec 2015. Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	(1)	(2)	(3)	(4)	(5)	(6)
	High VIX			Low VIX		
Panel A: VIX	The most undervalued	The most overvalued	Undervalue - Overvalue	The most undervalued	The most overvalued	Undervalue - Overvalue
CPE 1	0.47%	-0.03%	0.50%	0.04%	-0.18%	0.22%
	(6.3)	-(0.4)	(11.3)	(0.9)	-(4.9)	(8.6)
CPE 2	0.55%	0.07%	0.48%	0.11%	-0.13%	0.24%
	(7.2)	(1.1)	(10.7)	(3.0)	-(3.4)	(8.6)
CPE 3	0.55%	0.07%	0.48%	0.12%	-0.13%	0.24%
	(7.2)	(1.1)	(11.2)	(3.3)	-(3.4)	(8.7)
	High Financial Stress			Low Financial Stress		
Panel B: CFSI	The most undervalued	The most overvalued	Undervalue - Overvalue	The most undervalued	The most overvalued	Undervalue - Overvalue
CPE 1	0.37%	-0.09%	0.46%	0.15%	-0.12%	0.26%
	(4.8)	-(1.3)	(10.7)	(3.3)	-(2.6)	(8.8)
CPE 2	0.48%	0.02%	0.46%	0.18%	-0.07%	0.25%
	(6.3)	(0.2)	(10.3)	(4.5)	-(2.0)	(8.6)
CPE 3	0.47%	0.01%	0.46%	0.19%	-0.08%	0.27%
	(6.3)	(0.2)	(10.6)	(4.7)	-(2.0)	(8.9)
	High EPU			Low EPU		
Panel C: EPU	The most undervalued	The most overvalued	Undervalue - Overvalue	The most undervalued	The most overvalued	Undervalue - Overvalue
CPE 1	0.31%	-0.11%	0.42%	0.20%	-0.10%	0.30%
	(4.5)	-(1.9)	(10.3)	(4.2)	-(2.2)	(10.1)
CPE 2	0.38%	-0.03%	0.41%	0.28%	-0.03%	0.31%
	(5.7)	-(0.5)	(10.4)	(5.9)	-(0.7)	(9.4)
CPE 3	0.39%	-0.03%	0.41%	0.28%	-0.03%	0.31%
	(5.8)	-(0.5)	(11.0)	(6.0)	-(0.8)	(9.3)

Table 7. Predict stock markets returns using CPE. This table reports the result of predicting cross-section *stock market returns* using CPE. The portfolio sorting approach is conducted based on daily, weekly, and monthly frequencies. To form portfolios, at each period t, I sort *stock returns* into five quintile portfolios using lagged CPE (form the smallest to the biggest). The equal-weighted result and value-weighted result are reported in Panel A and Panel B repsectively. The portfolios are rebalanced at the end of each period. The long-short stock portfolio returns between the highest CPE and the lowest CPE are reported in column "H-L". Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	Panel A: equal weighted panel						**Panel B: value weighted panel**					
	Low CPE	2	3	4	High CPE	H-L	Low CPE	2	3	4	High CPE	H-L
Daily												
CPE 1	0.05%	0.04%	0.04%	0.05%	0.06%	0.01%	0.01%	0.03%	0.03%	0.03%	0.05%	0.03%
	(1.62)	(1.89)	(1.97)	(2.42)	(2.02)	(0.84)	(0.48)	(1.70)	(1.95)	(1.68)	(2.03)	(2.50)
CPE 2	0.03%	0.04%	0.04%	0.05%	0.06%	0.03%	0.00%	0.03%	0.03%	0.04%	0.04%	0.04%
	(1.14)	(2.08)	(2.47)	(2.46)	(2.02)	(2.64)	-(0.07)	(1.76)	(1.79)	(2.32)	(1.48)	(2.91)
CPE 3	0.03%	0.04%	0.04%	0.05%	0.06%	0.03%	0.00%	0.03%	0.02%	0.03%	0.04%	0.03%
	(1.19)	(2.11)	(2.43)	(2.36)	(2.04)	(2.68)	(0.01)	(1.75)	(1.57)	(1.78)	(1.36)	(2.56)
Weekly												
CPE 1	0.17%	0.20%	0.20%	0.22%	0.28%	0.11%	0.03%	0.14%	0.17%	0.16%	0.18%	0.15%
	(1.26)	(1.99)	(2.28)	(2.49)	(2.25)	(1.92)	(0.21)	(1.55)	(2.40)	(2.11)	(1.96)	(1.66)
CPE 2	0.16%	0.19%	0.20%	0.25%	0.27%	0.11%	0.01%	0.16%	0.15%	0.21%	0.17%	0.16%
	(1.25)	(2.24)	(2.45)	(2.51)	(1.96)	(2.41)	(0.06)	(2.25)	(2.07)	(2.39)	(1.37)	(2.52)
CPE 3	0.16%	0.21%	0.19%	0.24%	0.27%	0.11%	0.04%	0.16%	0.12%	0.17%	0.16%	0.12%
	(1.29)	(2.40)	(2.42)	(2.40)	(1.92)	(2.31)	(0.27)	(1.81)	(1.82)	(2.02)	(1.35)	(1.96)
Monthly												
CPE 1	1.08%	0.87%	0.90%	0.98%	0.88%	-0.19%	0.48%	0.72%	0.72%	0.66%	0.49%	0.01%
	(2.00)	(2.33)	(2.94)	(2.69)	(1.79)	-(0.81)	(0.96)	(2.22)	(2.75)	(1.77)	(1.16)	(0.05)
CPE 2	1.06%	0.84%	0.86%	0.95%	0.99%	-0.07%	0.50%	0.64%	0.63%	0.68%	0.81%	0.31%
	(2.43)	(2.51)	(2.55)	(2.36)	(1.81)	-(0.27)	(1.37)	(2.18)	(1.89)	(1.72)	(1.64)	(1.09)
CPE 3	1.03%	0.88%	0.92%	0.89%	0.98%	-0.05%	0.58%	0.69%	0.63%	0.53%	0.78%	0.20%
	(2.27)	(2.58)	(2.97)	(2.19)	(1.78)	-(0.19)	(1.19)	(2.07)	(2.60)	(1.31)	(1.50)	(0.63)

Table 8. Predict corporate bond markets returns using CPE. This table reports the result of predicting *corporate bond returns* using lagged CPE. I compute the bond return at individual bond level by Bond Return$_{i,j,t} = P_{i,j,t}/P_{i,j,t-1} - 1$. Next I conduct the equal-weighted scheme to aggregate individual bond level data to firm level data. The portfolio sorting approach is conducted based on daily, weekly, and monthly frequencies. To form portfolios, at each period t, I sort *bond returns* into five quintile using lagged CPE (form the smallest to the biggest). The equal-weighted result and value-weighted result are reported in Panel A and Panel B repsectively. The portfolios are then rebalanced at the end of each period. The long-short portfolio of bond returns between the highest CPE and the lowest CPE are reported in column "H-L". Newey-west t-statistics are reported in the brackets. The sample period is from Jan 2001 to Dec 2015.

	Panel A: equal weighted panel						**Panel B: Value weighted panel**					
	Low CPE	2	3	4	High CPE	H-L	Low CPE	2	3	4	High CPE	H-L
Daily												
CPE 1	0.03%	0.03%	0.01%	0.03%	0.04%	0.01%	0.07%	0.09%	0.04%	0.04%	0.06%	-0.02%
	(1.53)	(2.14)	(0.98)	(1.98)	(1.70)	(0.47)	(4.12)	(5.14)	(4.23)	(3.31)	(3.48)	-(0.96)
CPE 2	0.03%	0.01%	0.02%	0.02%	0.05%	0.02%	0.06%	0.01%	0.10%	0.07%	0.05%	-0.01%
	(1.92)	(0.67)	(1.59)	(1.20)	(1.96)	(1.24)	(4.78)	(1.90)	(5.68)	(4.21)	(2.58)	-(0.50)
CPE 3	0.02%	0.02%	0.01%	0.04%	0.05%	0.03%	0.04%	0.04%	0.02%	0.14%	0.06%	0.02%
	(0.76)	(1.40)	(0.62)	(2.55)	(1.95)	(1.64)	(2.69)	(3.40)	(2.36)	(7.24)	(3.02)	(1.31)
Weekly												
CPE 1	0.13%	0.11%	0.07%	0.10%	0.18%	0.04%	0.34%	0.39%	0.17%	0.19%	0.26%	-0.08%
	(1.29)	(1.64)	(1.16)	(1.34)	(1.45)	(0.55)	(3.18)	(3.31)	(3.08)	(2.70)	(2.46)	-(0.70)
CPE 2	0.12%	0.02%	0.12%	0.09%	0.20%	0.08%	0.26%	0.06%	0.49%	0.27%	0.25%	-0.01%
	(1.51)	(0.43)	(1.79)	(1.04)	(1.53)	(1.01)	(3.54)	(1.45)	(3.89)	(2.92)	(2.06)	-(0.15)
CPE 3	0.04%	0.08%	0.04%	0.19%	0.20%	0.16%	0.17%	0.16%	0.09%	0.65%	0.26%	0.10%
	(0.57)	(1.38)	(0.59)	(2.16)	(1.53)	(1.35)	(1.86)	(2.58)	(2.12)	(5.07)	(2.09)	(0.99)
Monthly												
CPE 1	0.55%	0.58%	0.20%	0.40%	0.73%	0.18%	1.19%	1.76%	0.55%	0.87%	1.09%	-0.10%
	(1.22)	(1.93)	(0.84)	(1.20)	(1.34)	(0.59)	(2.17)	(2.69)	(2.43)	(2.22)	(2.05)	-(0.18)
CPE 2	0.47%	0.17%	0.41%	0.44%	0.81%	0.34%	1.15%	0.26%	1.94%	1.16%	1.07%	-0.08%
	(1.35)	(0.71)	(1.39)	(1.22)	(1.33)	(0.76)	(2.96)	(1.30)	(2.12)	(2.40)	(1.68)	-(0.16)
CPE 3	0.15%	0.34%	0.17%	0.82%	0.81%	0.67%	0.53%	0.72%	0.32%	2.65%	1.15%	0.62%
	(0.49)	(1.22)	(0.74)	(2.09)	(1.35)	(1.70)	(1.28)	(2.23)	(1.89)	(2.99)	(1.82)	(1.24)

Table 9. Predict put options market returns using CPE. This table reports results of predicting *put options returns* using CPE. I conduct a panel regression rather a portfolio sorting to test the predictability of CPEs on options returns because of the complex price structure of options dataset. The regression specification is:

$$\mathrm{R}_{i,j,t+1} = \alpha + \beta_1 \mathrm{CPE}_{j,t}/10000 + \beta_2 \mathrm{TTM}_{i,j,t} + \beta_3 \mathrm{Moneyness}_{i,j,t} + \beta_4 \mathrm{Strike} + \beta_5 \mathrm{Implied\_Vola}_{i,j,t-1}$$
$$+ \beta_6 \mathrm{BA\_spread}_{i,j,t-1} + \beta_7 \mathrm{Open\_Interest}_{i,j,t-1} + g_j + \epsilon_{i,j,t+1}$$

where i is option contracts, j is firm, and t is date. TTM is time-to-maturity for each option contract, Moneyness is ratio of strike over spot price, Strike is strike price of options contract, implied Vola is option implied volatility, BA spread is 0.5*(bid price+offer price), g_j indicates the option contract fixed effect dummies. The standard errors for the specification are clustered by date. R indicates *put options returns* respectively. ***,**, and * denote significant at the 1%, 5%, and 10% level respectively and numbers in the parentheses are T-statistics. The sample period is from Jan 2001 to Dec 2015.

	(1) putr	(2) putr	(3) putr	(4) putr	(5) putr	(6) putr
Lag_CPE1	-0.311***			-0.017		
	(-3.11)			(-0.20)		
Lag_CPE2		-0.021***			-0.027***	
		(-3.43)			(-3.93)	
Lag_CPE3			-0.026***			-0.037***
			(-3.59)			(-4.23)
TTM				-0.018***	-0.018***	-0.018***
				(-12.66)	(-13.14)	(-13.14)
Moneyness				0.251***	0.248***	0.248***
				(20.75)	(21.65)	(21.66)
Strike				0.000***	0.000***	0.000***
				(22.78)	(22.73)	(22.73)
Lag1putr				-0.000***	-0.000**	-0.000**
				(-2.78)	(-2.46)	(-2.46)
Lag2putr				-0.000	-0.000	-0.000
				(-1.51)	(-1.30)	(-1.30)
Lag3putr				-0.000	-0.000	-0.000
				(-0.37)	(-0.58)	(-0.58)
Lag4putr				0.000	0.000	0.000
				(0.39)	(0.12)	(0.12)
Lag5putr				0.000	0.000	0.000
				(1.06)	(0.91)	(0.91)
Lag_Implied_Vola				-0.080***	-0.075***	-0.075***
				(-13.65)	(-13.51)	(-13.51)
Lag_BA_spread				-0.064***	-0.064***	-0.064***
				(-41.85)	(-42.49)	(-42.49)
Lag_open_interest				-0.000***	-0.000***	-0.000***
				(-22.94)	(-23.50)	(-23.49)
Intercept	0.003	0.003	0.003	-0.143***	-0.144***	-0.144***
	(1.48)	(1.49)	(1.50)	(-16.85)	(-17.65)	(-17.65)
Number of obs	40698641	43870839	43870839	32736462	35262928	35262928
R-sq	0.050	0.049	0.049	0.049	0.049	0.049
adj. R-sq	0.032	0.031	0.031	0.030	0.029	0.029
Contracts fixed effect	Y	Y	Y	Y	Y	Y
Cluster for SE (by day)	Y	Y	Y	Y	Y	Y

Table 10. Predict call options market returns using CPE. This table reports results of predicting *call options returns* using CPE. I conduct a panel regression rather a portfolio sorting to test the predictability of CPEs on options returns because of the complex price structure of options dataset. The regression specification is:

$$\mathrm{R}_{i,j,t+1} = \alpha + \beta_1 \mathrm{CPE}_{j,t}/10000 + \beta_2 \mathrm{TTM}_{i,j,t} + \beta_3 \mathrm{Moneyness}_{i,j,t} + \beta_4 \mathrm{Strike} + \beta_5 \mathrm{Implied\_Vola}_{i,j,t-1} + \beta_6 \mathrm{BA\_spread}_{i,j,t-1} + \beta_7 \mathrm{Open\_Interest}_{i,j,t-1} + g_j + \epsilon_{i,j,t+1}$$

where i is option contracts, j is firm, and t is date. TTM is time-to-maturity for each option contract, Moneyness is ratio of strike over spot price, Strike is strike price of options contract, implied Vola is option implied volatility, BA spread is 0.5*(bid price+offer price), g_j indicates the option contract fixed effect dummies. The standard errors for the specification are clustered by date. R indicates *call options returns* respectively. ***,**, and * denote significant at the 1%, 5%, and 10% level respectively and numbers in the parentheses are T-statistics. The sample period is from Jan 2001 to Dec 2015.

	(1) callr	(2) callr	(3) callr	(4) callr	(5) callr	(6) callr
Lag_CPE1	-0.012			-0.027*		
	(-0.77)			(-1.65)		
Lag_CPE2		-0.009			-0.008	
		(-1.09)			(-0.96)	
Lag_CPE3			-0.010			-0.009
			(-1.09)			(-0.91)
TTM				-0.007***	-0.007***	-0.007***
				(-8.47)	(-9.00)	(-9.00)
Moneyness				0.000	0.000	0.000
				(1.07)	(1.16)	(1.16)
Strike				0.000***	0.000***	0.000***
				(11.74)	(11.88)	(11.88)
Lag1callr				-0.001***	-0.001***	-0.001***
				(-3.49)	(-3.76)	(-3.76)
Lag2callr				-0.000***	-0.000***	-0.000***
				(-2.70)	(-2.59)	(-2.59)
Lag3callr				-0.000	-0.000**	-0.000**
				(-1.63)	(-2.06)	(-2.06)
Lag4callr				-0.000	-0.000	-0.000
				(-0.30)	(-0.73)	(-0.73)
Lag5callr				-0.000	-0.000	-0.000
				(-0.29)	(-0.87)	(-0.87)
Lag_Implied_Vola				-0.053***	-0.050***	-0.050***
				(-11.65)	(-11.74)	(-11.73)
Lag_BA_spread				-0.054***	-0.054***	-0.054***
				(-30.47)	(-31.27)	(-31.27)
Lag_open_interest				-0.000***	-0.000***	-0.000***
				(-16.13)	(-17.18)	(-17.18)
Intercept	0.014***	0.013***	0.013***	0.039***	0.038***	0.038***
	(9.35)	(9.57)	(9.58)	(11.95)	(12.11)	(12.10)
Number of obs	36348985	39560479	39560479	29249339	31840335	31840335
R-sq	0.049	0.049	0.049	0.044	0.045	0.045
adj. R-sq	0.031	0.031	0.031	0.024	0.025	0.025
Contracts fixed effect	Y	Y	Y	Y	Y	Y
Cluster for SE (by day)	Y	Y	Y	Y	Y	Y

Table 11. Leverage effect. This table reports results of predicting future stock risks using CPE based on regression approach. The stock volatilities are proxied by intraday realized volatility, $\sigma_{i,t}$ for each firm i each day t:

$$\Delta\sigma_{i,t+1} = \alpha + \beta\Delta\text{CPE}_{i,t} + X_{i,t}\gamma + \delta_j + e_{i,t+1}$$

where i $\in$ [1,N] indicates firm, t indicates day. $X_{i,t}$ is N by K matrix includes control variables such as stock returns, CDS returns, dollar volume of stocks, and stock market liquidity proxed by effective spreads (K=3 in this case). γ is K by 1 vector. δ_j is firm fixed effect. The standard errors of this regression are clustered by date. The sample period is from Jan 2002 to Dec 2013.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\sigma_{i,t+1}$	$\Delta\sigma_{i,t+1}$	$\Delta\sigma_{i,t+1}$	$\Delta\sigma_{i,t+1}$	$\Delta\sigma_{i,t+1}$	$\Delta\sigma_{i,t+1}$
ΔCPE $1_{i,t}$	-4.246***			-1.975***		
	(-4.57)			(-2.59)		
ΔCPE $2_{i,t}$		-0.955***			-1.650***	
		(-2.76)			(-5.36)	
ΔCPE $3_{i,t}$			-0.956***			-1.581***
			(-2.62)			(-4.90)
$\Delta\sigma_{i,t}$				-0.445***	-0.445***	-0.445***
				(-39.43)	(-39.43)	(-39.43)
Stock Return$_{i,t}$				-1.155***	-1.204***	-1.204***
				(-8.15)	(-8.48)	(-8.48)
CDS Return$_{i,t}$				0.301**	0.290**	0.289**
				(2.45)	(2.34)	(2.33)
Dollar Volume$_{i,t}$				-0.013***	-0.013***	-0.013***
				(-3.30)	(-3.27)	(-3.27)
Effective Spread$_{i,t}$				-2.524***	-2.524***	-2.524***
				(-11.18)	(-11.18)	(-11.18)
Intercept	-0.002	-0.002	-0.002	0.299***	0.297***	0.298***
	(-0.33)	(-0.33)	(-0.33)	(4.20)	(4.17)	(4.18)
Number of obs	1307381	1307381	1307381	1305380	1305380	1305380
R-sq	0.000	0.000	0.000	0.211	0.211	0.211
adj. R-sq	-0.000	-0.001	-0.001	0.211	0.211	0.211
Firm Fixed Effect	Y	Y	Y	Y	Y	Y
Cluster SE (by day)	Y	Y	Y	Y	Y	Y

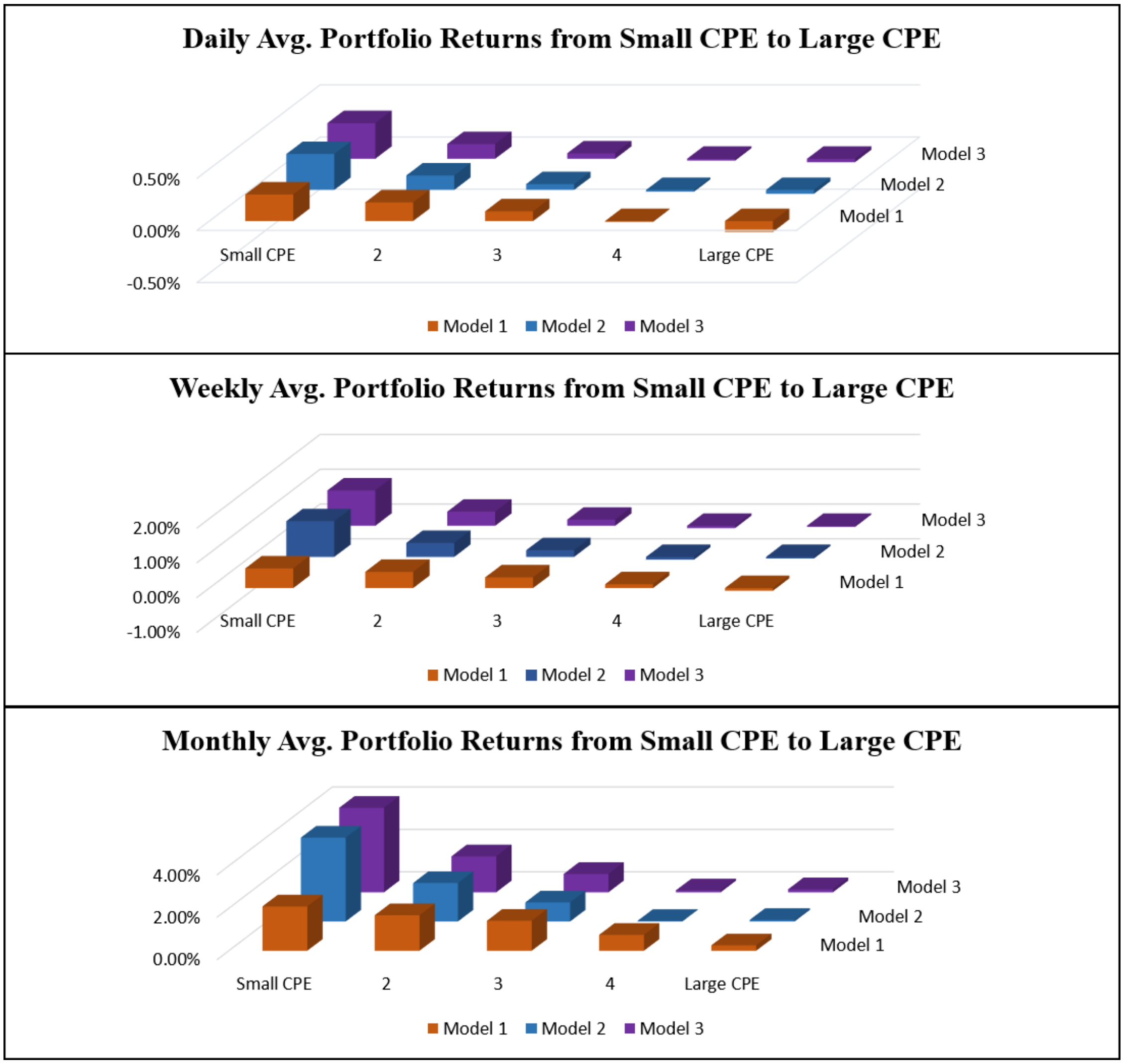

Figure 1. This figure plots the equal-weighted average CPE spread portfolio from the smallest CPE quintile to the largest CPE quintile for daily, weekly, and monthly respectively.

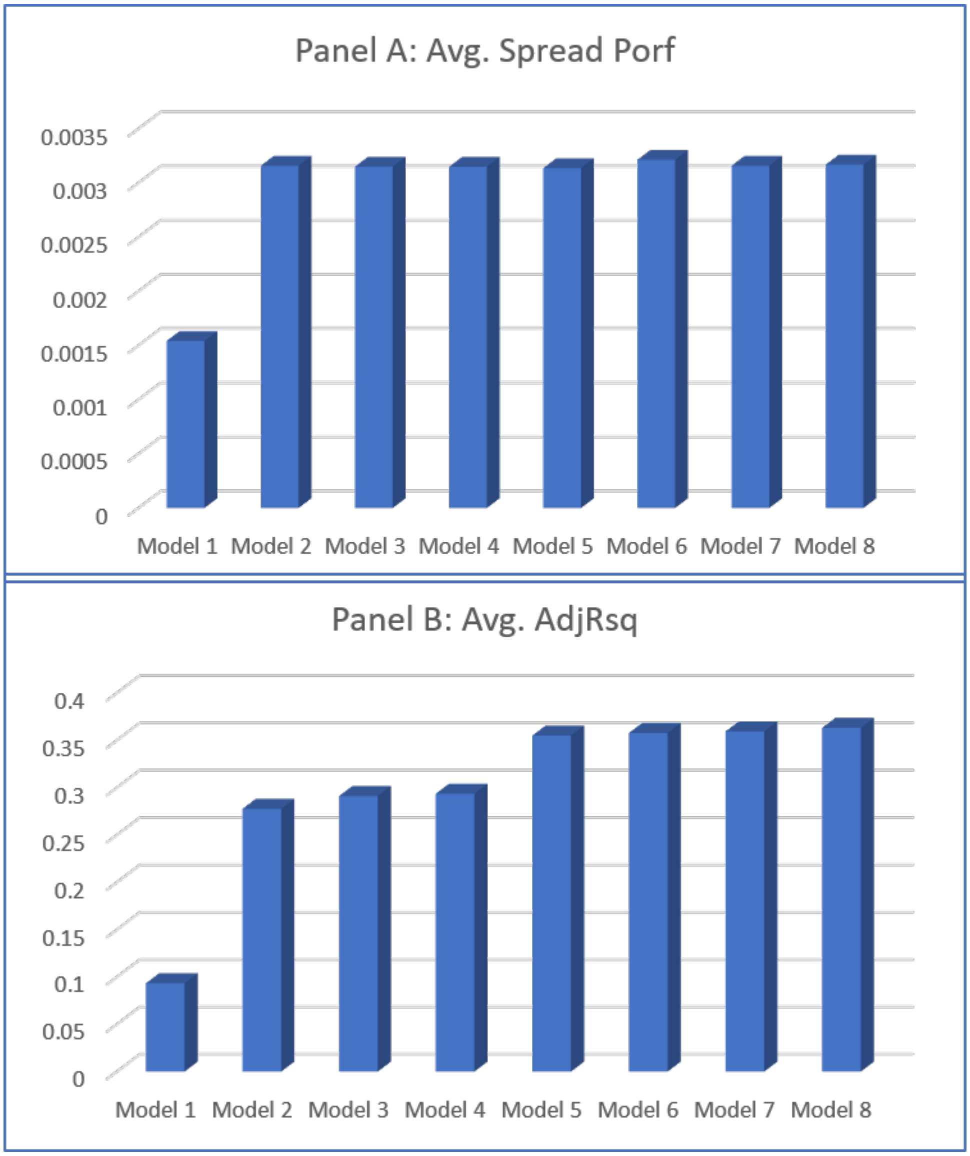

Figure 2. Panel A of reports the average spread portfolio of specification 1 to specification 8. Panel B is the time-series average adjusted cross-sectional R^2 of these 8 specifications or models.

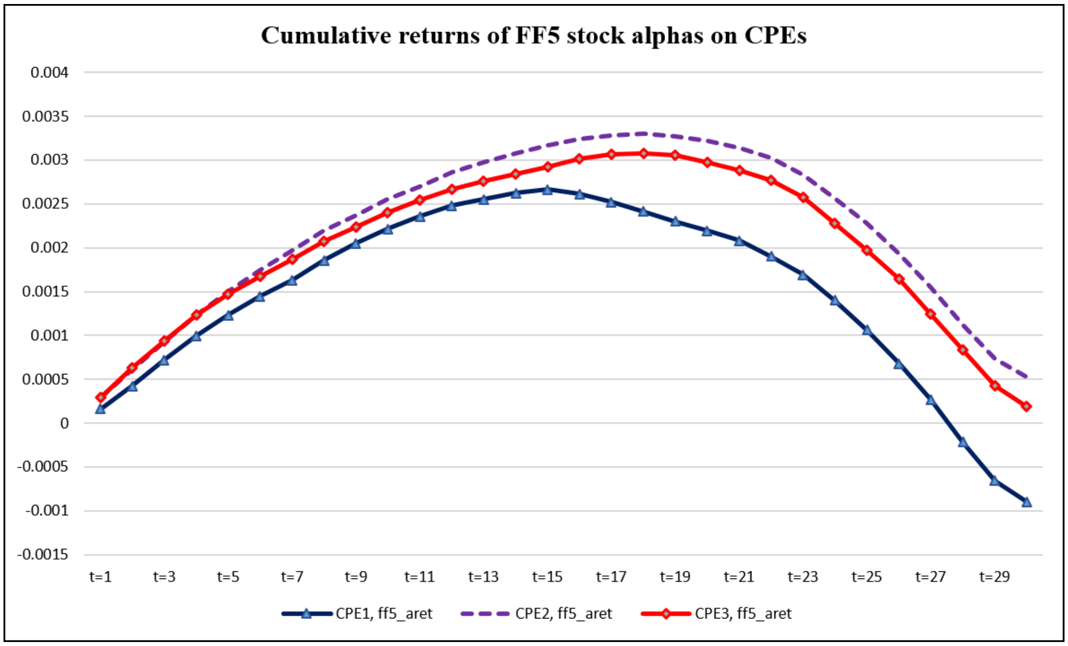

Figure 3. This figures reports the risk adjusted cumulative stock return (adjusted by Fama-French 5 factor model) of "H-L" strategies of spread portfolio of stock returns at day t using CPE information at t-1, t-2, t-3, ..., t-30 respectively. I plot the time-series average of alphas (from t-1 to t-30).

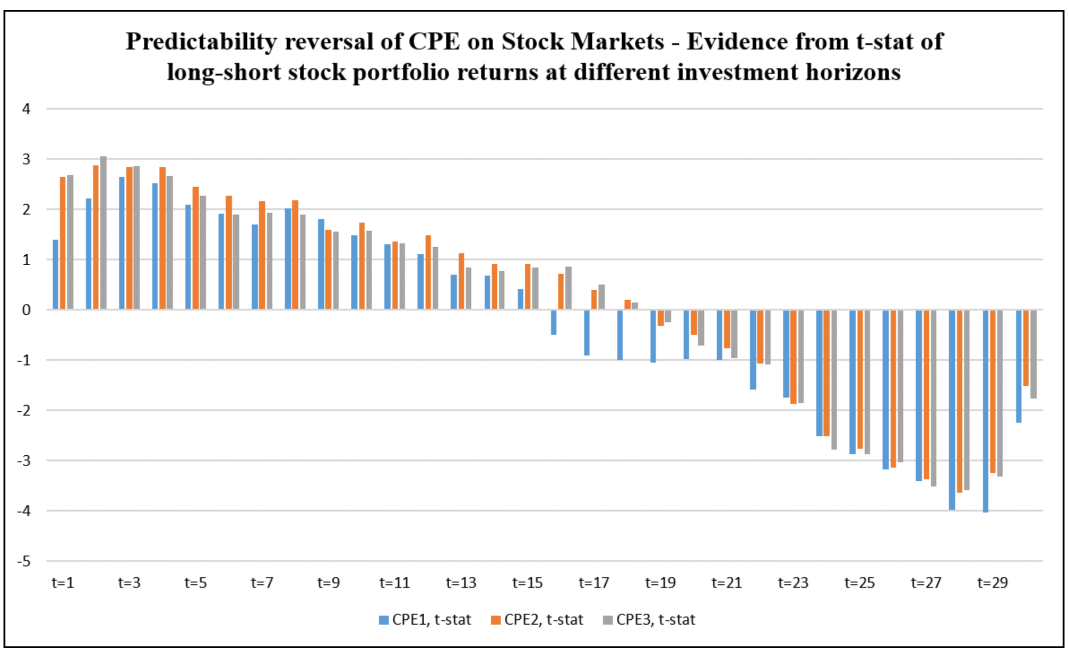

Figure 4. This figure plots the t-statistics of alphas (from t-1 to t-30) respect to CPE1, CPE2, and CPE3 reported in Figure 3.