# Stock Return Predictability of Cross-Market Deviations in Option Prices and Credit Default Swap Spreads*

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Cross-market deviations in (deep out-of-the-money) equity put option prices and credit default swap spreads of the same firm are temporary and predict future movements in the put options and credit default swaps (Carr and Wu, 2011). We document that large cross-market deviations also strongly relate to future equity prices of the reference firm. The paths of put option and equity prices are consistent with the perceptions implicit in the credit default swap history. Informed trading in credit default swaps partly explains this result. Our evidence also suggests that capital structure arbitrage activity caters for a legitimate alternative explanation.

***JEL* Classifications:** G11, G12, G13, G14, D8

**Keywords:** credit equity market integration, equity return predictability, capital structure arbitrage

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**Abstract**

Cross-market deviations in (deep out-of-the-money) equity put option prices and credit default swap spreads of the same firm are temporary and predict future movements in the put options and credit default swaps (Carr and Wu, 2011). We document that large cross-market deviations also strongly relate to future equity prices of the reference firm. The paths of put option and equity prices are consistent with the perceptions implicit in the credit default swap history. Informed trading in credit default swaps partly explains this result. Our evidence also suggests that capital structure arbitrage activity caters for a legitimate alternative explanation.

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# 1 Introduction

Cross-market information flow is a subject of widespread interest. From an academic standpoint, the study of trading on different venues (e.g. equities, bonds), or derivative instruments (e.g. options, credit default swaps), offers an excellent framework for testing hypotheses pertaining to information asymmetries. Regulators are also interested in the analysis of cross-market information flow. The analysis may identify cases where their intervention becomes necessary to prevent or uncover potentially fraudulent transactions; or may even stimulate discussions for the necessity of regulatory reforms. Additionally, investment professionals can benefit from identifying opportunities that arise due to temporary information delays in the prices of related assets.

An impressive range of researchers (we review this literature below) have empirically investigated the links between different trading venues, different derivative instruments, as well as cross-market links. The vast majority of these studies conclude that the price or trading in one asset can be informative for the price or trading in a related asset. This finding is consistent with the predictions of theoretical microstructure models such as Kyle (1985), and Glosten and Milgrom (1985) which suggest that the trading process reveals important information for the assets involved and affects the future paths of prices.

Articles in this literature typically focus on cross-market information flow between two securities only. One example is the study of whether trading of equity options of firm reveal information for the price of the firm's equity (Easley, O'Hara, and Srinivas, 1998). Another example is the investigation of whether severe changes in credit default swap spreads impact the value of the equity of the reference firm (Acharya and Johnson, 2007). A third example is the analysis of whether credit default swap spreads predict the default probability implicit in deep out of the money put options of the same firm and vice versa (Carr and Wu, 2011). Overall, the literature on cross-market information flow largely neglects that information may flow between more than two securities of the same firm. Information is expected to flow between three markets for example in the case of credit default swap, equity options, and the equity of the same firm, given their documented pairwise linkages.

Studying the linkages of all potentially related securities of the same firm has important implications on the inferences regarding future prices of these securities. More importantly,

instances of investor disagreement with respect to the prices of the related securities serve as a particularly attractive laboratory for the testing of hypotheses pertaining to informed trading. In this study we focus on the analysis of the credit default swap, the equity option, and the equity of the same firm. The current literature has documented pairwise information flow between these markets and has provided theoretical explanations for its existence. Building on this literature allows us to generate our priors for the path of future prices of the related securities, identify instances of disagreement, explore what pattern future valuations exhibit and explain why.

More specifically, we identify instances of investor disagreement through the link between deep out of the money put options and credit default swaps developed in Carr and Wu (2011, CW hereafter). We hypothesize that when these two securities – temporarily – trade in opposite directions, they potentially reflect different perceptions about the fundamentals of the firm. These, implicit, perceptions have been documented to strongly correlate with future equity returns when studied separately. The purpose of this study is to reconcile *how* this contradicting information, *jointly* revealed in CDS and equity options markets, materializes in the cash equity market and explain *why*.

We base our analysis on CDS spreads and deep-out-of-the-money (DOOM hereafter) put options of the same firm. Following CW, we define a standardized credit contract to make CDS spreads and DOOM put option prices *directly* comparable from a theoretical viewpoint. This contract, termed a 'Unit Recovery Claim' (URC hereafter), pays off $1 if and only if default occurs before expiry. The value of this contract can be computed from the CDS spread. Since the URC can be replicated through DOOM put options, its value can also be computed from the prices of DOOM put options. We characterize as large cross-market deviations the occurrences of unusually large differences in current URC values obtained from DOOM put options and CDS on the same firm's debt.

We find that unusually large differences of URC values are only temporary and revert to their usual level shortly after they occur, on average within about one week. The process of reversion involves changes in the CDS and the equity option, and, as we show for the first time, also involves largely predictable changes in the equity values of the reference firm. Unusually large differences of URC values are also strongly economically related to future equity returns. In particular, our portfolio forming analysis concludes that spread portfolios of

stocks based on the magnitude of cross-market deviations of URC values from their usual level earn on average a risk-adjusted return of 36.3 basis points per week (20.73 percent annualized) with a t-statistic of 3.39. These results are confirmed with cross-sectional tests and survive several robustness checks.

Our principal finding is that large cross-market deviations in equity option prices and CDS spreads of the same firm contain important information for the firm's future equity price. The predictability we document is an integral, yet unattended, component of the predictability of cross-market deviations documented in previous work. We observe that large deviations in the relative pricing of equity options and CDS are on average followed by equity (option and spot) prices that are consistent with the price history of the CDS contract (and are contrary to the price history of the option prices). This is generally consistent with informed trading in credit markets. However we argue that informed trading in the CDS markets only partly explains the predictability pattern we document. An alternative, not mutually exclusive explanation, which suggests that capital structure arbitrage activity dictates the future path of equity (option and spot) prices, cannot be ruled out.

### 1.1 Related Literature

Cross-market information flow has been the subject of academic investigation from as early as the introduction of exchange traded options contracts in the 1970's. Black (1975) first argues that "...Since an investor can get more action for a given investment in options than he can by investing directly in the underlying stock, he may choose to deal in options when he feels he has an especially important piece of information …". Several studies have subsequently tested if this prediction is supported by actual data.[1] While the evidence in earlier studies is mixed, more recent studies provide sufficient evidence to conclude that option prices and trading activity in the options market predict future movements in the underlying equity returns. Ang, Bali, and Cakici (2010) highlight that the documented

[1] Examples include: Manaster and Rendleman (1982), Easley, O'Hara, and Srinivas (1998), Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), Roll, Schwartz, and Subrahmanyam, (2010), Xing, Zhang, and Zhao (2010), Cremers and Weinbaum (2010), Yan (2011). See Giamouridis and Skiadopoulos (2012) for a review of the more recent literature.

predictability in the short-term is consistent with the multimarket trading, sequential trade model of Easley, O'Hara, and Srinivas (1998); while the mid-term predictability can be economically interpreted through the demand-based option pricing models of Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2009).

Cross-market information flow has also been studied between CDS and cash equity markets. This literature is relatively new given that sufficiently large cross-sections and time-series of CDS data have only become available in recent years. Studies in this strand include Longstaff, Mithal, and Neis (2003), Acharya and Johnson (2007), Berndt and Ostrovnaya (2008), Forte and Pena (2009), Norden and Weber (2009), Qiu and Yu (2012) among others. The evidence in these studies is rather mixed. Forte and Pena (2009), and Norden and Weber (2009) conclude that the equity market leads the CDS market more frequently in the price discovery process, while Longstaff, Mithal, and Neis (2003) do not find a clear leader. Acharya and Johnson (2007) find evidence of information flow from the CDS market to the equity market before instances of extreme increases in the CDS spreads, which they attribute to insider trading. Berndt and Ostrovnaya (2008), and Qiu and Yu (2012) also find conditional (on extreme CDS moves) flow of information from the CDS to the cash equity market. Information heterogeneity is used as an argument to reconcile the results in these studies too.[2]

Another strand of literature that this paper is related to is the literature linking CDS and equity options markets. Several authors (e.g. Hull, Nelken, and White, 2004; Carr and Wu, 2010) have argued that due to the common status of a firm's equity and its debt as contingent claims on the assets of the firm motivates why equity options and CDS written on the same reference company should be valued jointly. Cao, Yu, and Zhong (2010), among others linking implied volatility with credit risk, find that individual firms' put option-implied

[2] Related, although to a lesser extent, to the line of research investigating the association of equity and credit are papers that have been concerned with the the effect of default risk on equity returns. Examples include Dichev (1998), Vassalou and Xing (2004), Avramov et al. (2007), Garlappi, Shu, and Yan (2008), Campbell, Hilscher, and Szilagyi (2008), Da and Gao (2010), George and Hwang (2010). A recent paper by Friewald, Wagner, and Zechner (2011) nicely reconciles the inconclusive evidence in this literature and suggests that firms' equity returns and Sharpe ratios increase with credit risk premia.

volatility dominates historical volatility in explaining the time-series variation in CDS spreads. A novel paper by CW, establishes a simple robust link between CDS and DOOM American-style equity put options. The predictions of their model are empirically confirmed. Cllectively the analysis in CW concludes that deviations in the prices of the two insurance contracts are temporary and forecast future movements in the put options and the CDS. Berndt and Ostrovnaya (2008) also conclude that there is information flow from the CDS market to the options market and vice versa. Conrad, Dittmar, and Hameed (2011) in another recent paper find that default probabilities estimated through equity options and CDS of the same firm present with strong correlation, especially post the Global Financial Crisis.

Finally, this paper also relates to the capital structure arbitrage[3] literature. A key paper in this literature is Yu (2006). He provides a thorough presentation and analysis of the capital structure arbitrage strategy at the level of individual trades that involve simultaneous positions in the CDS and the equity of the same firm. He concludes that portfolios of capital structure arbitrage trades produce attractive Sharpe ratios, similar to those obtained with other types of fixed-income arbitrage strategies and hedge fund industry benchmarks. Duarte, Longstaff, and Yu (2007) also investigate the risk and return attributes of capital structure arbitrage. CW refer to a trading strategy that resembles the characteristics of capital structure arbitrage when they discuss the concept of selling CDS and buying DOOM puts of the same firm to hedge the credit risk. Kapadia and Pu (2010) is another recent paper that uses the concept of capital structure arbitrage to study the integration of equity and credit markets. They conclude that a convergence trading strategy - that involves positions on the CDS and the equity of a firm - on the average firm earns an excess return of 1.04% over a 1-month

[3] Duarte, Longstaff, and Yu (2007) define capital structure arbitrage as a class of fixed-income trading strategies that exploit mispricing between a company's debt and its other securities (such as equity). It is one of the most popular relative-value strategies within the hedge fund industry. Fixed-income arbitrage invested capital amounts for 13.3% of the U.S. $2.48 trillion of hedge fund assets as estimated by eVestment/HFN and Citi ICG analytics in November 2011. Duarte, Longstaff, and Yu (2007) point out the total amount of capital devoted to fixed-income arbitrage is likely much larger than that reported in hedge fund databases due to their limited coverage and also due to the fact that many other firms directly engage in proprietary fixed income arbitrage trading.

horizon. Buraschi, Trojani, and Vedolin (2011) also study capital structure arbitrage in the context of investor disagreement.

Relative to these works our main contribution is to provide a thorough and rigorous investigation of *how* the *joint* information discovery in the CDS and option markets materializes in the cash equity market and explain *why*. We carry out our analysis with the entire spectrum of cross-market deviations – not just negative events. We are particularly concerned with the economic significance of cross-market information flow between these three markets as well as with the duration of economically important information revelation. These are issues that have not been studied in prior works. What additionally makes our investigation more robust and, distinct, from prior analyses is that we incorporate real-life transaction cost data in our analysis. Berndt and Ostrovnaya (2008) is the only study we know that investigates the information flow between CDS and options markets, as well as the joint contribution of these markets to the price discovery in the stock market in the context that we also do. Berndt and Ostrovnaya (2008) reach several important conclusions that we reflect on, but is different than ours in many repsects.[4] Tang and Yan (2007) also study the three markets

[4] We highlight three main differences. First, in our investigation of price discovery in the CDS and options markets we make use of directly (or more) comparable prices, i.e. URC values based on CDS spreads and DOOM puts. We believe that this choice allows us to compare how the two markets price similar outcomes for the firm's equity price within an as similar as possible time horizon. In Berndt and Ostrovnaya (2008) the option market information is captured through standardized 60-day at-the-money options (this practice is followed in other studies too, e.g. Buraschi, Trojani, and Vedolin, 2011, Cao, Yu, and Zhong, 2010), which are very liquid instruments and hence more reliable in terms of the information they convey. However we argue that these options are not likely to be used by extremely bearish market participants or by market participants wishing to hedge against severe negative price jumps. Hence they are less likely to impound views similar to those impounded in CDS spreads. Second, in our analysis the relationship between CDS spreads and option prices is governed by strong theoretical foundations, i.e. arbitrage conditions. Berndt and Ostrovnaya (2008) motivate the relationship between CDS spreads and option prices on theoretical grounds; however they introduce material structure to this relationship through the econometric specification they estimate to purify the information obtained in the CDS, options, or equity markets. Third, our analysis is carried out in a period when – for at least

jointly focusing on potential liquidity spillovers from the equity and the equity option markets to the CDS market.

Our second contribution is that we further study the link between equity option and CDS and, more importantly, provide new insights for the process of reversion of the two securities after the occurrence of large cross-market deviations. We extend the analysis of CW to a broader cross-section of firms and a longer period of time that also includes the Global Financial Crisis. We document for the first time that it takes on average about one week for the cross-market deviation to revert from either extreme back in the range defined by roughly the 25$^{th}$ and the 75$^{th}$ percentiles. This conclusion provides additional empirical support for the link developed in CW; cross-market deviations characterized through their link constitute mispricing and are only temporary. Kapadia and Pu (2010) also reach the conclusion that equity and credit market disintegration is due to mispricing. Our evidence finally also complements that of Berndt and Ostrovnaya (2008), and Conrad, Dittmar, and Hameed (2011), who also investigate the linkages of the CDS and the equity options markets.

Our third contribution relates to the literature on information discovery in options markets. The overall conclusion in this literature suggests that abnormal increases in put implied volatilities (e.g. Ang, Bali, and Cakici, 2010) or put trading (e.g. Easley, O'Hara, and Srinivas, 1998; Pan and Poteshman, 2006; Roll, Schwartz, and Subrahmanyam, 2010) are negative predictors of the future move of equity prices. Our contribution over the existing literature is to show that in the presence of a traded CDS on the firm's debt, and in instances of CDS and DOOM put option prices disagreement, these predcitions are not confirmed ex post. In partciular, we document that large deviations in the relative pricing of the two securities are on average followed by equity prices that are consistent with the price history of the CDS contract (and are contrary to the price history of the put option contract).

Finally, we contribute to the capital structure arbitrage literature and also provide useful clues to investment professionals engaging in capital structure arbitrage or equity market

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the second half of it – neither CDS spreads nor option price changes have been moderate. Berndt and Ostrovnaya (2008) recognize that one disadvantage in their framework is that moderate move in rates – as those observe in their study period - will be recognized as adverse credit events for the firm even though the change in spreads most likely did not signal a drastic deterioration of its credit quality.

neutral stretegies. Our empirical analysis suggests that the measure we use for cross-market deviations is sufficient to identify instances of potentially profitable capital structure arbitrage trades. This measure may serve as an alternative to the measures used in Kapadia and Pu (2010) or Yu (2006). Moreover, our analysis suggests that such opportunities, which may simply occur because the equity price reacts too slowly to new information (Yu, 2006), can be exploited in the equity market alone. The transaction cost analysis with real-life data we carry out is the first to our knowledge in this context.

The rest of this article is organized as follows. Section 2 demonstrates the link between equity option prices and CDS spreads. Section 3 provides the details of our sample and the selection process we follow. Section 4 conducts exploratory analysis to get qualitative insights on the potential information flow from the CDS and option markets to the cash equity markets. Section 5 presents the results of the cross-section and time-series analyses that investigate the economical and statistical significance of the information content of equity option prices and CDS spread deviations. Section 6 reports the results of a number of robustness checks. Section 7 presents an interpretation of the results, and Section 8 concludes.

## 2 The link between DOOM Puts and CDS

In order to link American-style DOOM puts and CDS we implement the CW approach. CW proposed a simple and robust link between equity American-style DOOM put options and a credit insurance contract on the same reference company. In their setting, the stock price is bounded below by a strictly positive barrier $B > 0$ before default, but drops below a lower barrier $A<B$ at default, and stays below $A$ thereafter. The range *[A, B]* defines a default corridor in which the stock price can never reside. Given the existence of the default corridor, they showed that a spread between any two American-style DOOM put options of the same maturity and with strike prices falling within the default corridor, i.e. a long position in the high strike put option combined with a short position in the low strike put option, replicates a pure credit insurance contract that pays off when and only when the company defaults prior to the option expiry. Should this spread be scaled through the difference in the strike prices, the payoff becomes one unit – hence it is termed a URC. The URC price is:

$$UR^{p}\left(t,T\right)=\frac{P(K_2,T)-P(K_1,T)}{K_2-K_1} \qquad (1)$$

where the superscript *p* denotes the information source as American put options on the underlying stock, *t* and *T* denote the time the URC price is computed and the maturity of the put option respectively, $P(K_2,T)$, $P(K_1,T)$ are the put option prices for the contracts replicating the credit insurance contract with strike prices $K_2>K_1$.

Alternatively, credit insurance can be bought through CDS. Assuming fixed and known bond recovery rate (*R*), constant interest rate (*r*) and fixed default arrival rate ($\lambda$) as in CW, we can compute the URC value from a single CDS spread as:

$$UR^c(t,T) = \xi k \frac{1-e^{-[r(t,T)+\xi k](T-t)}}{r(t,T)+\xi k}, \quad \xi = 1/(1-R) \tag{2}$$

where the superscript *c* denotes the information source as CDS written on the corporate bond of a firm and *k* is the CDS spread which according to the earlier assumptions is known to have a flat term structure, proportional to the default rate, i.e. $k = \lambda(1-R)$. $r(t,T)$ denotes the time *t* continuously compounding spot interest rate for the period *t* to *T*. For simplicity we refer to $UR^p(t,T)$ and $UR^c(t,T)$ as $UR_t^p$ and $UR_t^c$ respectively hereafter.

## 3 Sample selection and Data construction

The sample period of our study is January 2004 to September 2010. We source options data from OptionMetrics and CDS data from CMA.[5,6] Equity returns data and company fundamental data are obtained through CRSP and Compustat respectively.

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[5] The OTC nature of CDS may cast skepticism on whether CMA provides the most accurate CDS information for our analysis. A recent paper by Mayordomo, Pena, and Schwartz (2010), argues that CMA quotes lead the price discovery process in comparison with the quotes provided by other databases, such as GFI, Fenics, Reuters EOD, Markit and JP Morgan.

[6] CMA receives CDS spreads from a range of market contributors. These contributors consist of both buy and sell side institutions active in the fixed income markets such as asset managers, hedge funds and banks. These active market participants provide CMA with both real-time and delayed prices of executed trades, firm or indicative bid/offers on specific entities (e.g. company or emerging market), tenors, seniorities (ranking of the debt receiving moneys in case of default) and restructuring types (definition of what constitutes a default, ISDA agreement types). To ensure the highest level of accuracy, CMA checks these prices against previous quotes and validates those using related securities and news. For less liquid entities where market activity is infrequent,

We apply a number of filters to minimize the impact of recording errors. Following CW, on each day we look through the options data to select a list of companies with put options that satisfy the following criteria: (1) the bid price is greater than zero; (2) the open interest is greater than zero; (3) the mid price is lower than the strike price of the option, $K$; (4) the mid price is not lower than $K - S$, where $S$ is the current spot price of the option's underlying equity; (5) The ask price is greater than or equal to the bid price; (6) The bid-ask spread is greater than or equal to \$0.05 for mid price less than \$3, and the bid-ask spread is greater than or equal to \$0.1 for mid price greater than or equal to \$3 (following Goyal and Sarreto, 2009); (7) the time-to-maturity is greater than or equal to 360 days; and (8) the absolute value of the put option Delta is not greater than 0.15. For companies with multiple put options that satisfy the above criteria, we choose the put option with the highest open interest. If two or more options have the same open interest we select the option with the lowest moneyness. We define moneyness as $K/S$.

Following CW we identify the default corridor $[A, B]$ ex-ante by assuming that the stock price drops to zero upon default, i.e., $A = 0$. Thus, we set the lower of the two strikes in the put spread to zero so that we only need a single put to create the desired payoff. To locate the strike of this put option and to ensure that the chosen strike is below the upper barrier $B$, in addition to the low (absolute) Delta criterion, we require the option to have low moneyness.[7] Following the characterization of out-of-the money options in several studies (e.g. Xing,

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CMA calculates the fair CDS spread using a proprietary issuer/sector curve model that derives an appropriate curve using known liquid CDS spreads, bond spreads and ratings data. Illiquid reference entities are considered those for which CMA parses fewer than three email quotes. See the CMA documentation for additional information.

[7] CW require that the option has a low strike, i.e. below \$5, instead of the option having low moneyness. Our approach to locate the upper barrier $B$ increases our cross-section of observations dramatically without materially changing the strong time-series co-movements of the two sets of URC values. In particular, the low Delta/low strike criteria (CW) sources 44,210 option contracts for analysis. The low Delta criterion alone, qualifies 111,982 option contracts for further analysis which are reduced to 111,907 when we apply the low moneyness filter. In terms of the time-series co-movements of the two sets of URC values, when options are obtained with the low Delta/low strike criteria the full sample correlation of the URC values is 0.712 (p-value=0.000) and it is 0.707 (p-value=0.000) when options are obtained with the low Delta/low moneyness criteria (CW, report a cross-correlation of 0.703 in their sample).

Zhang, and Zhao, 2010; Doran and Krieger, 2010), we set the moneyness threshold equal to 0.95.

We repeat the above procedure every trading day and for every company in order to select the put option that satisfies our criteria. Once the put option is selected we compute the values of URC from both American puts on a company's stock and 5-year CDS spreads on the same company's corporate bonds according to equations (1) and (2). This choice implies a flat term structure of CDS spreads which may introduce bias. We investigate the potential impact of this bias in subsection 6.1. We assume a fixed and known bond recovery rate of 40% as in CW.[8] $r(t,T)$ is computed with the assumption that it is piecewise constant, technically, through interpolation of US dollar LIBOR and swap rates which we obtain from Bloomberg. We use senior unsecured USD-denominated CDS. To address liquidity concerns and monitor the quality of the information we obtain from the CDS market, we exclude CDS spread observations that have remained unchanged for five or more days. Additional filters are applied once URC values are obtained as in CW.

When we apply the full range of the above filters, we obtain a sample of 258 companies with broad sector coverage.[9] The number of companies on a trading day, determined by the number of companies for which we can compute URC values from both CDS and put option contracts, ranges from 5 (which occurs in two trading days in the entire sample) to 138, with an average of 60 companies per trading day. Table 1 reports summary statistics for our sample. Panel A reports summary statistics for the sample firms' characteristics, Panel B

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[8] The 40% recovery rate assumption is based on long-term historical averages; see for instance the discussion in Guo, Jarrow and Lin (2009). Using shorter estimation horizons, Elkamhi, Jacobs, and Pan (2010) find that the average recovery rate is around 50%. Conrad, Dittmar, and Hameed (2011) report a much higher recovery rate of 65.8% on average (with 27% standard deviation), which they compute use the joint information in option-implied default probabilities and CDS-implied default probabilities. We carry out our analysis with the 40% recovery rate assumption to allow comparisons of our results with CW when possible. We also provide baseline results for analysis based on a 50% recovery rate assumption.

[9] The industry split of our sample based on the Fama and French classification of 10 industrial sectors is as follows: Consumer Non-Durables 10 firms, Consumer Durables 3 firms, Manufacturing 37 firms, Energy 23 firms, HiTec Business Equipment 17 firms, Telecoms 19 firms, Shops 33 firms, Health 13 firms, Utilities 19 firms, and Other 92 firms.

reports the sample firms' options contracts characteristics, and Panel C reports the sample firms' CDS contracts characteristics.

**[Table 1 about here]**

The median market capitalization is U.S. $4.90 billion, the median book value of debt is U.S. $3.36 billion, and the median ratio of total debt to book value of equity is 97% (the median ratio of total debt to market value of equity is 78%). Most firms in our sample are large and hence trading in their equity market is quite liquid, i.e. the median turnover is 1.43% of the outstanding shares per day. The median (annualized) stock return idiosyncratic volatility based on daily stock returns is 27.3% with a $90^{th}$ percentile of 56.9% and a $10^{th}$ percentile of 14.5%. The median stock implied volatility is 56.3% when it is obtained from DOOM put options, while it is 43% when we use at-the-money put options with the same maturity to imply it. The options we use in our analysis are options with median moneyness of 0.523 and a $90^{th}$ percentile moneyness of 0.657 suggesting that the vast majority of put options we use are far out-of-the money options. The median CDS level is 256 basis points with a $90^{th}$ percentile of about 707 basis points and a $10^{th}$ percentile of 133 basis points. The distribution of CDS levels indicates that the median firm has been trading in reasonable CDS levels for corporates in the period we examine. The median S&P credit rating of the firms in sample is BB.

# 4 The predictability of cross-market deviations: put options and CDS

We start our empirical analysis with the investigation of the relationship between cross-market deviations and future CDS spreads, and put option prices. Our objective is to improve our understanding of the joint information/price discovery in the CDS and option markets and explore the nature of the relative mispricing identified by the cross-market deviation measure. We start by defining our basic measure of cross-market deviations and discuss its empirical properties. Next, we study its predictability over future price movements in the corresponding put and CDS contracts as in CW. We extend their analysis, however, in two important ways. First, we account for the fact that cross-market deviations may additionally depend on

liquidity in the markets involved;[10] and second we carry out the analysis with a much richer, both in the cross-section and in the time-series, dataset. Finally, for the first time, we explore the time-series of the URC values obtained from the options and the CDS market before and after the observation of large cross-market deviations (event study).

### 4.1 A simple measure for cross-market deviations

Cross-market deviations may occur for several reasons. Kapadia and Pu (2010) for example find that equity market illiquidity contributes to equity and CDS markets disintegration. They argue that existing or potential funding constraints (and liquidity), and other costs associated with cross-market trading may prevent equity and CDS markets from restoring their usual parity (e.g. Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Pontiff, 1996, 2006). Buraschi, Trojani, and Vedolin (2011) document also that larger belief heterogeneity increases credit spreads and their volatility, and contributes to the disintegration of the equity and CDS markets.

To take these considerations into account, we propose the following measure:

$$URCS_DEV_t = \left[ (UR_t^p - UR_t^c) - mean(UR^p - UR^c) \right] \qquad (3)$$

where $mean(UR^p - UR^c)$ is measured over a two-month period. We argue that a short-term historical average value incorporates relevant current information thus determining a usual level of cross-market deviation under the prevailing market conditions. With this choice we believe we minimize the impact of limits to arbitrage and measurement errors associated with the valuation of URCs on the characterization of cross-market deviations as usual or unusual. Our analysis in subsections 4.2 and 4.3 confirms this conjecture.

Measures of unusual market conditions in the spirit of ours have been used in other studies too. Berndt and Ostrovnaya (2008), and Qiu and Yu (2012) for example characterize a

[10] For example, if an investor wants to build her portfolio with the equity options and the CDS contracts, she may not trade the CDS contract at all if her stock option position is too costly to build due to illiquidity. Tang and Yan (2007) find significant liquidity spillover from bond, stock, and option markets to the CDS market. Qiu and Yu (2012) find that CDS liquidity is a key determinant of the amount of information flow from the CDS to the equity market.

change in the CDS that exceeds its mean plus four standard deviations as a credit event. Yu (2006) defines a variable that measures mispricing between equity and CDS markets. He considers levels beyond two standard deviations in excess of its historical mean sufficient to trigger a capital structure arbitrage strategy. Finally, Kapadia and Pu (2010) investigate the predictability of a cross-market disintegration measure during days of extreme – as classified by an in-sample average - equity market movements. Relative to these measures, ours is simple, has sound theoretical underpinnings and does not suffer from look-ahead bias.

$URCS_DEV_t$ exhibits interesting empirical properties. The average (cross-sectional) mean $URCS_DEV_t$ is -0.00048 and the average (cross-sectional) median value is -0.00094. The 5%, 25%, 75%, and 95% percentiles are -0.03428, -0.01127, 0.00987, and 0.03510 respectively. The median $URCS_DEV_t$ has a minimum value of -0.06461 and a maximum value of 0.06822. The distribution of $URCS_DEV_t$ exhibits slightly positive skew due to a small number of extreme (large) values observed during the Fall of 2008. Figure 1 plots the time series of $URCS_DEV_t$ over the study period.

**[Figure 1 about here]**

### 4.2 Pooled regressions

We proceed with the investigation of the predictability of cross-market deviations over future price movements in the corresponding put and CDS contract. We define $D_t = (UR_t^p - UR_t^c)$ and orthogonalize it with respect to various company, option, CDS, and liquidity[11] characteristics $X_t$ through the following time-series regression:[12]

$$D_t = a + bX_t + \delta_t \qquad (4)$$

[11] Our measures for stock and option liquidity are rather standard. To measure CDS liquidity we use the bid-ask over the mid quote which has been used in some studies (e.g. Acharya and Johnson, 2007; Tang and Yan, 2007). More recent works use instead the number of quote providers (Friewald, Wagner, and Zechner, 2011; Qiu and Yu, 2012). Friewald, Wagner, and Zechner (2011) find however that the two measures are empirically similar.

[12] Unreported analysis of the cross-market deviation of the URC value estimates rejects the null of non-stationarity.

This analysis uses daily data over the past two-month period to calculate the residual $\delta_t$. Note that $URCS_DEV_t$, the measure we define in equation (3), is equivalent to $\delta_t$ when we set $X_t = 1$ in equation (4). Next, we perform pooled (cross-sectional and time-series) regressions where the regression residual $\delta_t$ is used to predict future unit recovery claim value movements, as follows:

$$UR^p_{t+\Delta t} - UR^p_t = \alpha^p + \beta^p \delta_t + e_{t+\Delta t} \quad (5)$$

and

$$UR^c_{t+\Delta t} - UR^c_t = \alpha^c + \beta^c \delta_t + \eta_{t+\Delta t} \quad (6)$$

We conjecture that the null $\beta^p = \beta^c = 0$ is consistent with the hypothesis that the residual $\delta_t$ conveys no information.

**[Table 2 about here]**

Table 2 reports estimates of the coefficients in equations (5) and (6). Our analysis focuses on the predictability of cross-market deviations over one- and four-week forecasting horizons. The conclusions from this analysis can be summarised as follows. When the two markets deviate from each other, the deviation predicts future movements in both markets to the direction of their future convergence. The results indicate that URC values sourced from equity put options are more sensitive to the deviation of the two markets than URC values obtained through CDS spreads. For example for $URCS_DEV_t$ (top row), we observe that over a one-week forecast horizon, the $\beta^p$ = -0.225 (se=0.007) and the $\beta^c$ = 0.048 (se=0.005). This pattern prevails in the entire Table and conforms to the argument of Berndt and Ostrovnaya (2008) that changes in option prices are much more sudden than changes in the CDS spreads due to more often trading of the former on unsubstantiated rumours. The predictability of cross-markets deviations is not explained away by firm, equity option, CDS or liquidity characteristics. Overall, our analysis conludes that the results in CW hold in the extended sample as well as after we account for liquidity. Moreover, the measure of cross-market deviations we propose is qualitatively as effective in predicting future moves in CDS and equity options as other measures that account also for various company, option, CDS, and liquidity characteristics.

### 4.3 Event study

To shed light on the paths of CDS and equity option prices before and after observing a large cross-market deviation in the URC values obtained from the two markets we conduct an event study. We argue that if large cross-market deviations are due to information delays or heterogeneous beliefs, URC values obtained from the two markets should diverge (converge) prior to (post) the occurrence of the large cross-market deviation. If on the other hand deviations are either due to violations of the model and/or implementation assumptions, we do not expect to observe any distinct pattern.

We focus on large cross-market deviations. In our baseline investigation, we characterize an observed deviation as large if it falls in the top/bottom one third of the cross-section distribution of *URCS_DEV*. Firms are grouped in tercile portfolios based on their ranking with respect to their *URCS_DEV*. We then monitor the evolution of URC value changes, i.e. the cross-sectional average URC value change in the portfolio, in the period preceding the reference point of time by up to one month until one month post the reference date. We do that for URC values obtained through equity put options as well as for URC values obtained through CDS spreads and report the results for a weekly rebalance in Figure 2. Panel A reports the average cumulative change in URC values for portfolios of stocks with low *URCS_DEV* (bottom one third) and Panel B reports the average cumulative change in URC values for portfolios of stocks with high *URCS_DEV* (top one third).

**[Figure 2 about here]**

Panel A and Panel B provide very interesting insights. In the pre-event period, we observe that URC values obtained from CDS and DOOM put options move in the opposite directions. Therefore, if the CDS and options markets are examined independent of each other, they reveal different perceptions. For example, in Panel A, we observe that over the days that precede a large cross-market deviation occurrence, URC values obtained through CDS increase (cumulatively). The current literature (e.g. Acharya and Johnson, 2007; Berndt and Ostrovnaya, 2008; Qiu and Yu, 2012) suggests that CDS increases are genearlly negatively correlated with future equity returns. Over the same period, URC values obtained through DOOM put options decrease (cumulatively). Decreasing put option prices are associated with positive future returns (e.g. Ang, Bali, and Cakici, 2010).

The post-event patterns of URC value changes are opposite to their respective pre-event patterns and hence also opposite to each other. The only exception is the pattern of CDS changes after the occurrence of large negative cross-market deviations. The results from the event-study are consistent with the predictions of the pooled regression model. There are two important new findings though. First, URC values revert to their usual relative levels through a process that is relatively smooth and is not dictated on average by large jumps. Second, and more important, the process of reversion is different in the two extreme cross-market deviation portfolios. This is a pattern that we document for the first time and is rather critical in our explanation of the predictability of cross-market deviations over future equity returns that we discuss below. We observe the same pre- and post-event patterns when we repeat the analysis with $\delta_t$ obtained through all alternative specification of equation (4).

Collectively, this section finds that discrepancies of the current cross-market deviation of URC values and their usual level are significant predictors of future URC values. This predictability is not explained away by firm, equity option, CDS or liquidity characteristics. Our event study analysis suggests that prior to the observation of large cross-market devations, CDS and put option prices move on average in opposite directions. Post the event, CDS and put option prices move in order to restore their fair relative valuations. These findings are robust to the measure of cross-market deviation we use. Hence we maintain our basic measure, that is $URCS_DEV_t$ in equation (3), for the rest of the paper.

# 5 The predictability of cross-market deviations: equity returns

The earlier analysis indicates that the occurrence of large cross-market deviations is the result of significant price changes in the CDS and the equity options markets and that those deviations predict future movements in both markets due to the future convergence. CDS, equity options, and the equity of the same firm are however related securities. Provided that pairwise linkages have been documented in the litarture, we expect that cross-market deviations predict future movements in cash equity markets too. To investigate this conjecture we perform standard cross-sectional and portfolio forming analysis in subsections 5.1 and 5.2 respectively. In subsection 5.3, we examine the decay of the predictability of cross-market deviations.

### 5.1 Fama-MacBeth Regression

We conduct cross-sectional return predictability tests (Fama and McBeth, 1973) by means of three different specifications, all based on the following generic specification:

$$RET_{i,t} = b_{0,t} + b_{1,t} URCS_DEV_{i,t-1} + \sum_{i=2}^{n} b_{i,t} CONTROLS_{i,t-1} + e_{i,t} \qquad (7)$$

where $RET_{i,t}$ is firm *i*'s return for week[13] *t*, $URCS_DEV_{i,t-1}$ is the normalized cross-market deviation for firm *i* on week *t-1* defined in equation (3) with averaging over the past two months, and $CONTROLS_{i,t-1}$ are the *n*-1 control variables for firm *i* observed at week *t-1*. The three different specifications we consider involve an implementation of equation (7): i) without any control variables (specification [1]); ii) with controls for firm size, book-to-market ratio, and previous 1-month return, (specification [2]); and iii) with controls for firm size, book-to-market ratio, the previous 1-month return, Chang, Christoffersen, and Jacobs (2010) skewness measure, and Amihud's (2002) illiquidity measure (specification [3]).

Firm size and book-to-market controls are typical controls in the literature. We choose to control for short-term momentum as opposed to a longer-term momentum variable given the nature of cross-market deviations, i.e. temporary, expected to reverse in the short-term. We use the skewness measure proposed by Chang, Christoffersen, and Jacobs (2010) which is based on the option market to capture the market skewness risk premium, documented in Harvey and Siddique (2000), Conrad, Dittmar, and Ghysels (2009), and Chang, Christoffersen, and Jacobs (2010). Chang, Christoffersen, and Jacobs (2010) show that this measure is more effective than others based on the stock market. Finally, we use Amihud's (2002) factor which has been shown in the literature to be predictive of the future cross-section of equity returns.

**[Table 3 about here]**

[13] Like Hou and Moskowitz (2005), Cremers and Weinbaum (2010), and CW among others, we compute returns between adjacent Wednesdays rather than Mondays or Fridays. Friday-to-Friday returns have high autocorrelations, while Monday-to-Monday returns have low autocorrelations (e.g. Chordia and Swaminathan, 2000).

Table 3 reports coefficient estimates, i.e. averages of weekly estimates, along with t-statistics obtained with the Newey-West (1987) adjustment. The coefficient 0.0024 (t-statistic=3.71) in the first column of Table 3 suggests that a one-standard deviation change in *URCS_DEV* is associated with a weekly return of 24 basis points (13.28 percent annualized). The results reported in the second column of Table 3 suggest that the predictability of *URCS_DEV* is independent of the predictability of other well-known factors predicting the cross-section of equity returns. The coefficient 0.0020 (t-statistic=3.20) suggests that even after controlling for size, book-to-market, and short-term momentum effects, the predictability of *URCS_DEV* remains economically and statistically significant. The alternative risk-adjustment approach of specification [3] also indicates that the predictability of *URCS_DEV* over the subsequent week returns is significant, i.e. the coefficient is 0.0017 (t-statistic=2.93).[14]

We now take a closer look at the coefficients in the control variables as estimated through specification [2]. The size variable carries a negative and only marginally significant coefficient, i.e. -0.0012 (t-statistic=-1.63). The sign of the coefficient is consistent with the size effect. The large capitalization of the firms in our sample, the relatively poor performance of the size factor over our specific sample period of 2004 to 2010, and the short-term nature of the investigation of predictability could possibly explain why the size effect is not stronger. The coefficients of the BM and MOM variables are both insignificant. In specification [3], the coefficient of SKEW is negative but insignificant, i.e. -0.0377 (t-statistic=-0.88), consistent with a negative correlation between return and skewness. The coefficient of illiquidity is positive but insignificant, i.e. 1.5801 (t-statistic=0.74).

A possible concern for the genuine drivers of the cross-market deviation predictability is non-synchronicity. Evidence that deviations in URC values contain information not yet incorporated in the prices of the underlying securities could simply reflect the fact that CDS, option, and stock price quotes are not observed at the same point of time. Option markets close at 4:02 PM Eastern Standard Time (EST), stock exchanges close at 4:00 PM EST, and

[14] These results are obtained with a 40% recovery rate assumption. With a 50% recovery rate assumption we obtain qualitatively similar results. In particular one-standard deviation change in *URCS_DEV* is associated with a weekly return of 21 basis points (t-statistic=3.68), 21 basis points (t-statistic=3.68), and 21 basis points (t-statistic=3.68) as specifications [1], [2], and [3] indicate respectively.

CDS quotes are snapshots obtained at 5:00 PM EST. Xing, Zhang, and Zhao (2010), and Cremers and Weinbaum (2010) among others raise this issue in their analysis that involves options and underlying equities and conduct their tests also by assuming that: (a) purchases and sales of stocks take place at the opening of trading on the day after the signal is observed, thus ignoring the first overnight return (Cremers and Weinbaum, 2010), and (b) purchases and sales of stocks take place at the close of trading on the day after the signal is observed, thus ignoring the first day return (Xing, Zhang, and Zhao, 2010).[15]

When we conduct analysis (available on request) to examine the impact of non-synchronicity of the quotes on our results we find that the predictability of *URCS_DEV* deteriorates, however it remains highly economically and statistically significant. In particular, when we assume that the sales and purchases of stocks take place at the opening of trading on the day after the signal is observed, the factor coefficients for specifications [1], [2], and [3] are 0.0022 (t-stat=3.60), 0.0018 (t-stat=3.09), and 0.0016 (t-stat=2.86) respectively. When we assume that purchases and sales of stocks take place at the close of trading on the day after the signal is observed the factor coefficients for specifications [1], [2], and [3] are 0.0017 (t-stat=3.04), 0.0011 (t-stat=1.98), and 0.0009 (t-stat=1.67) respectively. These results suggest that the non-synchronicity of the price quotes does not explain the predictability of cross-market deviations.

Summarizing, the cross-sectional evidence, we find that cross-market deviations in CDS spreads and equity put option prices are strongly related to future equity returns. The predictability holds even after controlling for firm and market characteristics and for the non-synchronicity of equity, options, and CDS prices. This evidence complements Berndt and Ostrovnaya (2008) who find information flow however only conditional on adverse credit events. The additional contribution over the existing literature is that we document that the

[15] We argue that both approaches are rather conservative. Barclay, Hendershott, and Jones (2008) for example stress that the opening price must be determined with little or no trading at a time when uncertainty about fundamental values is high and hence opening a financial market creates unusual stress. They also argue that this stress is compounded when there are large order imbalances at the open, even if these order imbalances are unrelated to changes in fundamental values. Ignoring the first day return on the other hand may also be critical given the nature of the phenomenon we study and the short horizon we expect it to last for.

joint information discovery in equity options and CDS markets manifests itself in the cash equity markets in a way that is economically significant.

### 5.2 Portfolio Forming Approach

In this subsection we demonstrate the predictability of *URCS_DEV* using the portfolio formation approach. Every week we compute *URCS_DEV* for every firm and sort stocks in tercile portfolios. We then compute the subsequent week portfolio returns and estimate the following time-series regression:

$$RET_{p,t} - RF_t = b_0 + b_1 EXMARKET_t + b_2 SMB_t + b_3 HML_t + b_4 MOM_t + b_5 SKEW_t + u_{i,t} \qquad (8)$$

In equation (8), $RET_{p,t}$ is the return of the portfolio of stocks in each tercile over one week, $RF_t$ is the short-term risk-free rate at time *t*, $EXMARKET_t$, $SMB_t$, $HML_t$, and $MOM_t$ are the return of the market in excess of the short-term risk-free rate, the size, value, and 1-month momentum risk factors. We construct a systematic skewness factor as in Chang, Christoffersen, and Jacobs (2010) and denote it with $SKEW_t$. [16]

**[Table 4 about here]**

Panel A of Table 4 reports the characteristics for the portfolios sorted on *URCS_DEV*. The evidence in Panel A suggests that firms in the extreme *URCS_DEV* portfolios are similar in terms of their market capitalization, book-to-market, and stock market liquidity, but also in terms of the implied volatility of their options, and their CDS levels. We observe a monotonic pattern in terms of the last month return (decreasing), bid/ask spreads in put options (decreasing) and CDS (increasing). The pattern of last month return might be related to over- or under-reaction to public information or negligence/possession of non-public information. The patterns of bid/ask spreads provide important insights that we discuss in section 7.

To further understand the interaction of *URCS_DEV* with firm, option, and CDS characteristics, we compute the firm-level cross-sectional correlations of all the variables for

[16] We sort all stocks of the NYSE, AMEX, and NASDAQ into quintile portfolios according to their sensitivities to innovations in implied market skewness. $SKEW_t$ is the return of a portfolio that buys the stock with the lowest sensitivities, and sells the stock with the highest sensitivities, to innovations in implied market skewness.

each week from January 2004 to September 2010. Panel B of Table 4 reports the time-series averages of the cross-sectional correlations. Cross-market deviations present little correlation with the majority of the characteristics, which probably reflects the U-shaped relationship we documented in Panel A. The strongest correlation is observed between *URCS_DEV* and the put illiquidity measure, followed by the correlation with the last month return, the CDS level and the CDS illiquidity. These observations suggest for example that put options are more expensive than their respective CDS when their bid/ask spread is higher, the equity return of the reference firm over the past month and its CDS are higher, and the bid/ask spread of the CDS is lower.

We now turn to Table 5 where we present the weekly tercile portfolio excess returns of portfolios sorted on the basis of *URCS_DEV*. Each tercile portfolio contains on average about 20 stocks. This number rises significantly in the period August 2007 to September 2010 (see Table 11 below) to about 28 stocks. The 'Low Portfolio', which comprises stocks of firms with the lowest *URCS_DEV,* produces a weekly return in excess of the risk-free rate of -8.8 basis points (-4.68 percent annualized). The 'High Portfolio', which comprises stocks of firms with the highest *URCS_DEV,* produces a weekly return in excess of the risk-free rate of 31.8 basis points (17.95 percent annualized). Hence, the 'Low Portfolio' underperforms the 'High Portfolio' by a weekly return in excess of the risk-free rate of 40.6 basis points (23.45 percent annualized).

**[Table 5 about here]**

When we adjust for risk through equation (8), alphas[17] for the 'Low Portfolio' and 'High Portfolio' are -21.7 basis points per week (-11.93 percent annualized) and 14.5 basis points per week (7.82 percent annualized) respectively. If we buy the 'High Portfolio' and short the 'Low Portfolio' the alpha of the long/short strategy is 36.3 basis points per week (20.73 percent annualized) with a t-statistic of 3.39.[18] The contribution of the 'Low Portfolio' to the

[17] We term 'alphas' the estimate of the intercept in equation (8), which essentially is the risk-adjusted return.

[18] These results are obtained with a 40% recovery rate assumption. With a 50% recovery rate assumption we obtain qualitatively similar results. If we buy the 'High Portfolio' and short the 'Low Portfolio' the alpha of the long/short strategy is 35.4 basis points per week (20.17 percent annualized) with a t-statistic of 3.55.

alpha is higher than that of the 'High Portfolio' in the entire period, although the contribution of the latter is economically large.[19]

We now take a closer look at the coefficients in the risk factors and the risk/reward characteristics of the tercile portfolios. The long/short strategy described earlier presents with insignificant exposure to market risk, and statistically negligible bias to size and value. The negative loading on momentum, i.e. -0.239 (t-statistic=-3.43) indicates that the long/short strategy encompasses a reversal strategy. This observation provides additional evidence that the deviations in URC values are temporary and hence prices should revert shortly to reflect no arbitrage conditions. The Sharpe and Information (not reported) Ratios are 1.33 and 1.24 respectively. Over the same period the reward to risk ratios for the aggregate market, a small minus big firms long/short strategy, a high minus low book-to-market firms long/short strategy, and a 1-month reversal strategy were 0.15, 0.24, 0.26, and 0.20 respectively.

We complement our analysis with an examination of the impact of non-synchronicity in the price quotes as we did in section 5.1. When we assume that the sales and purchases of stocks take place at the opening of trading on the day after the signal is observed, the spread portfolio generates a risk-adjusted return of 27.5 basis points per week (15.35 percent annualized) with a t-statistic of 2.51. When we assume purchases and sales of stocks take

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[19] We conduct additional analysis to investigate whether significant returns can be obtained after accounting for transaction costs. We obtain transaction costs data from Citigroup Investment Research. Transaction costs are calculated through an impact cost model which measures equity trades impact as a power law of block size, with specific dependence on trade duration, daily volume, volatility and shares outstanding. The model is detailed in Almgren et al. (2005). Over the period of our study the impact cost data we use in our analysis suggest that the average of the transaction cost we subtract from each security return in the long/short portfolio is about 22 basis points. The respective average bid/ask spread (as a percentage of the mid-price) is about 13 basis points. We find that the alpha of a long/short strategy that invests USD 1 million on each security of the portfolio (equally-weighted portfolio) is 24.8 basis points per week (13.75 percent annualized) with a t-statistic of 2.30 after transaction costs are taken into account. Also, we find that the alpha becomes marginally insignificant when the strategy invests USD 3 million on each security of the portfolio (equally-weighted portfolio). We highlight that while statistical and economic significance are not lost after we account for real-life transaction costs, we consider our analysis conservative at least in two fronts. First, in that it uses a very naïve portfolio construction strategy. Second, in that the transaction costs incorporated are more likely an upper bound of impact cost given the respective bid/ask spreads.

place at the close of trading on the day after the signal is observed, the risk-adjusted return of the long/short portfolio becomes 19.3 basis points per week (10.55 percent annualized) with a t-statistic of 2.00. These results suggest, as in the cross-sectional analysis, that although there is a drop in the estimated alphas (and a deterioration in their significance), they remain significant and hence we conclude that non-synchronicity cannot explain the predictability of *URCS_DEV*.

To summarize, we find that firms with large negative *URCS_DEV* underperform firms with large positive *URCS_DEV*. Therefore, when the put contracts are unusually more expensive (cheaper) than their CDS counterparts, i.e. unusually more expensive (cheaper) relative to how expensive (cheap) they have been on average in the past, equity markets react as if put contracts were overpriced (underpriced) and the underlying equity underpriced (overpriced). The return difference that can be obtained through this observation is economically large and statistically significant irrespective of our adjustment for transaction costs or of non-synchronicity in price quotes in the CDS, the options, and the stock markets. Our study is the first to show how to exploit disintegration in the credit and equity markets, solely in equity markets.

### 5.3 How Long Does the Predictability Last?

In subsections 5.1 and 5.2 we find that *URCS_DEV* provides economically and statistically significant predictability for the cross-section of equity returns over a period of one week. In this subsection we examine whether this prediction lasts over longer horizons. Mitchell, Pedersen, and Pulvino (2007) argue that while arbitrage is reasonably fast when market participants are not capital constrained, it can be slow following major capital dislocations. Closer to the setting we conduct our investigation, Kapadia and Pu (2010) argue that pricing discrepancies across firms' equity and credit markets are related to impediments to arbitrage. If the stock market is very efficient in incorporating the information contained in *URCS_DEV*, the predictability would be temporary and unlikely to persist over a long period.

We first conduct an event study where we monitor the evolution of *URCS_DEV*, for deviations observed for firms in the top (large positive) and bottom (large negative) terciles portfolios. Our aim is to shed light on the average time these deviations take to revert to the normal levels and hence become uninformative for equity prices. Figure 3 illustrates the time

evolution of the average cross-market deviation when it is negative (Panel A), and when it is positive (Panel B). The evidence in Figure 3 combined with descriptive statistics of *URCS_DEV* (unreported) which suggest that the 25% and 75% of *URCS_DEV* are -0.01127, 0.00987 respectively, strikingly suggest that it takes on average about one week for the cross-market deviation to revert from either extreme back in the 25% to 75% range.

**[Figure 3 about here]**

We additionally conduct cross-sectional as well as portfolio forming analysis to investigate this issue in a setup similar to subsections 5.1 and 5.2. Table 6 reports results for the portfolio formation approach.[20] The results are obtained using the same approach as in subsection 5.2, however portfolios are now also held for two, three, and four weeks. The spread return over the second week is 2.3 basis points (t-statistic=0.20), over the third week -16.4 basis points (t-statistic=-1.56), and over the fourth week -2.3 basis points (t-statistic=-0.20). We note that the risk-adjusted return of the spread portfolio becomes insignificant after the first week and even reverses in the third week. The results from the cross-sectional analysis are similar and all together support the conclusion that the stock market is fast in incorporating information embedded in cross-market deviations of equity option and CDS prices.

**[Table 6 about here]**

In summary, this subsection finds that it takes about one week for *URCS_DEV* to revert back to its 'normal' levels. This is additional evidence that the deviations are more likely to be due to temporary information delays in either market. We also find that the economic significance of the predictability of *URCS_DEV* does not extend beyond the first week after its observation.

## 6 Robustness checks

In this section we investigate whether the predictability of cross-market deviations between equity option prices and CDS spreads we document so far is sensitive to various choices we make in our empirical framework.

[20] The results from the cross-sectional analysis are available on request.

### 6.1 Maturity mismatch

One of the main choices we have made in our analysis was to use CDS quotes from contracts with five years to maturity. This choice was made on the grounds that CDS at five years to maturity are the most liquid CDS contracts. However the majority of the options we used have a time to maturity between two and three years. In the case of options, trading volume is mostly concentrated in shorter maturity options (see Wei and Zheng, 2010). This maturity mismatch introduces bias and may have an impact on the conclusions of our analysis.

To address this issue, and under the constraint that there do not exist CDS at any maturity, we use an interpolation method to construct a term structure of different CDS. In this analysis we linearly interpolate CDS quotes for contracts with one, two, three, four, and five years to maturity to construct the term structure of different CDS. We then match the maturities between the options and the interpolated CDS. The correlation of the URC values obtained through American puts and CDS is 0.754 (p-value=0.000) for this sample. When we do not match the maturities of the CDS and the option contracts the full sample correlation of the URC values is 0.707. The firms we maintain for analysis are now 201 (were 258 before) and the option contracts we use are 66,159 (were 111,907 before). We conduct cross-sectional as well as portfolio forming analysis.

**[Table 7 about here]**

Table 7 presents the results from the portfolio forming analysis.[21] The results in Table 7 are similar with those presented in Table 5. The 'Low Portfolio' for example which comprises stocks of firms with the lowest *URCS_DEV* produces a weekly return in excess of the risk-free rate of -15.4 basis points (-8.8 basis points before). The 'High Portfolio' which comprises stocks of firms with the highest *URCS_DEV* produces a weekly return in excess of the risk-free rate of 30.4 basis points (31.8 basis points before). Hence, the 'Low Portfolio' underperforms the 'High Portfolio' by a weekly return in excess of the risk-free rate of 45.8 basis points (40.6 basis points before). Note that due to data availability the long/short portfolio strategy is implemented with 23.21 firms on average which is less than half the

[21] The results from the cross-sectional analysis are available on request.

number of firms used when we did not match the option and the CDS contract maturities. The results from the cross-sectional analysis are similar.

The evidence gathered in this subsection suggests that, while the maturity mismatch and the associated liquidity issues may raise theoretical concerns, their impact on the predictability of *URCS_DEV* is not severe; at least it is not severe enough so as to explain the predictability of *URCS_DEV* away.

### 6.2 Distress: Negative Book Value firms and Credit Rating impact

Negative book value firms are often regarded as firms in financial distress, with low probability of remaining in business for long. Jan and Ou (2008) find that of all Compustat firms (excluding financial and utility firms) the yearly average percentage of firms reporting negative book value has increased from 5% during 1976-85 to nearly 15% during 1996-2005. They also find that in the period 1976-2005, of all firms reporting losses, over 23% also reported negative book value concurrently. In our sample we observe on average 2.7 firms with negative book value per rebalance, i.e. 1 in the 'Low Portfolio', less than 0.6 in the middle portfolio, and 1.1 in the 'High Portfolio'.

If negative book value is attributed to financial distress[22] then it is natural to argue that the predictability of *URCS_DEV* could largely be influenced by these extreme cases. To rule out that our results are influenced by firms with negative book value of equity, we remove them and conduct cross-sectional as well as portfolio forming analysis. We report the results from the portfolio forming analysis in Table 8.[23] The results from this analysis suggest that our earlier conclusions are robust to the removal of firms with negative book value of equity.[24]

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[22] Jan and Ou (2008) argue that negative book values can be observed also for other reasons such as start-ups, large goodwill write-offs following business acquisitions, conservative accounting rules that lead to "undervalued assets", i.e. research and development (R&D) and advertising expenditures are two examples of potentially valuable intangibles that are hidden from the balance sheet.

[23] The results from the cross-sectional analysis are available on request.

[24] About 1 firm on average is included in the portfolio of stocks that should be shorted per rebalance period or 15 in total. From these firms, all except two continue their operations for many years after first reporting of negative

**[Table 8 about here]**

A more appropriate indicator of firm distress on the other hand is its credit rating. Norden and Weber (2009) argue that the information flow between equity and credit markets depends on the level of credit risk of the reference entity. Hence one might expect that the predictability of *URCS_DEV* could vary across firms with different credit ratings. To test this hypothesis we conduct a cross-sectional analysis where we condition on the credit ratings of the individual firms. This analysis pools weekly data and computes estimates of a panel regression for a specification similar to that described in equation (7). Results for this analysis are reported in Table 9.

**[Table 9 about here]**

The coefficient of the interaction variable, that is the variable DUMMYx*URCS_DEV*, where DUMMY equals 1 for non-investment grade firms, is negative and significant in all four specifications we consider. In sharp contrast, the coefficient of *URCS_DEV* is positive and significant in all four specifications we consider. Hence, it appears that one standard deviation move in *URCS_DEV* predicts a move in the subsequent week's firm returns of about 63 basis points for investment grade firms and of about 15 basis points for non-investment grade firms.

To sum up, we conclude that while the predictability of *URCS_DEV* is significant for all firms, it is stronger for firms rated as investment grade; these firms' rating in our sample is (on average) BBB+, while non-investment grade firms are (on average) rated BB. To the extent that the predictability of *URCS_DEV* can be attributed to more 'informed' CDS (relative to equity) quotes, this result can be easily reconciled. Qiu and Yu (2012) report that the CDS of firms near the investment-grade/speculative-grade boundary tend to be the most liquid. They argue that more liquidity is associated with more information flow from the CDS to the equity markets which is consistent with the argument of endogenous liquidity provision by 'informed' traders in the CDS market.

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book value. Furthermore, many of these firms' book values can remain negative for a prolonged period, i.e. 5 firms, or about 33% of the firms, operate in negative book values for the entire period post their first reported negative book value of equity. On the other hand, 8 firms, or about 53% of the firms, return to positive book value of equity after on average 6.6 quarters. Only two firms eventually defaulted.

### 6.3 Is the Information Contained in *URCS_DEV* unique?

The earlier analysis suggests that when *URCS_DEV* deviates from its 'normal' level, CDS spreads and put option prices move in order to resume to levels that are consistent with their expected levels. $UR^p$ changes however exhibit much higher (time-series) volatility than $UR^c$ changes, that is 0.282 vs. 0.090. This is also observed in Figure 2 which demonstrates that in the pre-event period $UR^p$ changes much more rapidly than $UR^c$. This phenomenon can be explained with the argument that options markets trade on unsubstantiated rumours more often than the CDS market does (Berndt and Ostrovnaya, 2008). It is thus possible that deviations in *URCS_DEV* are dominated by deviations in $UR^p$ and hence deviations in $UR^p$ alone could be as predictive as deviations in *URCS_DEV*. On the other hand deviations in $UR^c$ might be so informative, that even small changes may be able to predict future equity returns on their own. To test these conjectures we explore the predictability of each component of *URCS_DEV* separately. We conduct our analysis in a portfolio forming setting.

First, we examine the predictive ability of changes in DOOM put option prices and change in CDS spreads. To maintain consistency in the variables we define changes as in equation (3). That is:

$$URCS_DEV_t^p = \left[UR_t^p - mean(UR^p)\right] \quad (9)$$

$$URCS_DEV_t^c = \left[UR_t^c - mean(UR^c)\right] \quad (10)$$

In equations (9) and (10) $URCS_DEV_t^p$ and $URCS_DEV_t^c$ are the time-series deviations of URC values obtained through DOOM put option prices and CDS spreads respectively. Means are estimated over a two-month period. We find that stocks in the low $URCS_DEV_t^c$ portfolio outperform stocks in the high $URCS_DEV_t^c$ portfolio by a risk-adjusted return of 30.5 basis points per week (17.16 percent annualized) with a t-statistic of 2.38. Stocks in the low $URCS_DEV_t^p$ portfolio outperform stocks in the high $URCS_DEV_t^p$ portfolio by a risk-adjusted return of 19.0 basis points per week (10.37 percent annualized) with a t-statistic of 1.49.

We now use the returns of each of these long/short portfolios as additional risk factors when risk-adjusting the returns of the long/short portfolio based on *URCS_DEV*. If the

predictability of *URCS_DEV* is subsumed by either the predictability of $URCS_DEV_t^p$ or $URCS_DEV_t^c$, the respective alpha - estimated through the specification in equation (8) augmented with either of the two factors - will become insignificant. We present the results of this analysis in Table 10.

**[Table 10 about here]**

The results in Table 10 indicate that there is a strong correlation between the returns of the long/short portfolio obtained through *URCS_DEV* and the returns of the portfolios obtained through either $URCS_DEV_t^p$ or $URCS_DEV_t^c$. The respective beta coefficients are -0.204 (t-statistic=-3.48) and 0.417 (t-statistic=7.59). However, the risk-adjusted return of the long/short portfolio based on *URCS_DEV* remains significant and economically large even after accounting for the effect of either $URCS_DEV_t^p$ or $URCS_DEV_t^c$. In particular, when we risk-adjust for the effect of $URCS_DEV_t^p$ the alpha stays high at 34.5 basis points per week with a t-statistic of 4.08. When we risk-adjust for the effect of $URCS_DEV_t^c$ drops only slightly to 31.4 basis points per week with a t-statistic of 2.93. Interestingly, when we risk-adjust the return of the long/short portfolio based on $URCS_DEV_t^c$ with the return of the long/short portfolio based on *URCS_DEV*, its alpha vanishes. Hence we conclude that the predictability of *URCS_DEV* is not subsumed by the predictability of either of its components.

### 6.4 Sub-sample analysis

This section investigates whether the predictability of *URCS_DEV* is significant in certain periods of our sample and hence possibly drives the predictability we find in the whole sample. We divide our sample in two subsamples. The first covers the period January 2004 to July 2007. July 2007 has been argued to identify a critical turning point in the global capital markets, in particular given the quantitative investing meltdown in August 2007 (e.g. Conrad, Dittmar, and Hameed, 2011, Friewald, Wagner, and Zechner, 2011, Khandani and Lo, 2007, 2008).

We conduct both the cross-sectional and the portfolio forming analysis. Table 11 presents the results of the portfolio formation analysis for these two sub-periods.[25] Given the events of the Global Financial Crisis (GFC hereafter) in the second sub-period we report results also for August 2007 to September 2010 after we exclude the period of short selling ban in the US equity markets. This period is from July 21, 2008 to August 12, 2008, and from September 19, 2008 to October 8, 2008. Ni and Pan (2011) find that in the presence of short sale ban, it takes time for the negative information contained in either the options market or the CDS market to get incorporated into stock prices.

**[Table 11 about here]**

The results from this analysis indicate that the predictability of cross-market deviations is significant regardless of the sub-sample period examined and regardless of whether the short-selling ban period is included in the analysis. The minimum alpha is observed in the first period and it is 29.5 basis points per week with a t-statistic of 2.20. We reach similar conclusions with the cross-sectional analysis.

To get additional insight in the predictability of *URCS_DEV* across time, we plot the cumulative return of $1 invested in the hedge portfolio which is formulated weekly on the basis of the firms' *URCS_DEV*. We also plot the low and high *URCS_DEV* portfolio cumulative returns in excess of the market return, as well as the cumulative return of the market for the same period. We observe a consistent pattern over the entire sample period.

**[Figure 4 about here]**

This analysis concludes that the predictability of *URCS_DEV* has been strong in the entire sample period. The evidence suggests that it has been stronger in the more recent period. This is in our view due to two main reasons. The stronger co-movement of the two markets in the second sub-period due to deteriorating credit conditions. And also due to the fact that there has been an increased action in the two markets during this period and hence a larger cross-section of firms with which the predictability of *URCS_DEV* is investigated.

[25] The results from the cross-sectional analysis are available on request.

# 7 Interpretation of results

The preceding analysis suggests that large cross-market deviations contain information that predicts equity returns for up to about one week in a consistent way. Large negative (positive) cross-market deviations predict negative (positive) equity returns. This finding is statistically and economically significant, and robust to various tests we conducted. Before discussing our explanation of this phenomenon we explore the nature of firms for which unusually large deviations are observed. This will enlighten us further as to why cross-market deviations may occur. While a detailed investigation of this issue is beyond the scope of this paper, we will try to reflect on the conclusions of the current literature, the statistics reported in Table 4 as well as (unreported) evidence we obtain through additional analysis.

Perhaps the most comprehensive and rigorous study that we can reflect on is Buraschi, Trojani, and Vedolin (2011). They derive a theoretical model where investors have different perceptions of future cash flows and their degree of uncertainty, and empirically test the equilibrium link between belief heterogeneity, credit spreads and stock returns. Their conclusions suggest that larger belief heterogeneity increases credit spreads and their volatility, and implies a higher frequency of capital structure arbitrage violations. In fact, the properties of the firms in our extreme portfolios coincide with the properties of firms that are subject to large belief heterogeneity.

More specifically, Table 4 illustrates that the firms in the extreme portfolios are on average smaller than the firms in the mid portfolio. They have higher book-to-market ratios. They exhibit higher implied volatilities and their stock is more illiquid. In addition (unreported analysis) firms in the extreme portfolios exhibit higher standard deviations in earnings per share estimates and higher changes (over the previous and next one year) in their book value of debt relative to firms in the mid portfolio. Prior research (e.g. LaPorta et al., 1997; Diether, Malloy, and Scherbina, 2002; Sadka and Scherbina, 2007) has associated many of these attributes to uncertainty/differences of opinion. Finally, firms in either of the extreme portfolios have higher CDS and we find (unreported analysis) that they also experience more credit rating changes. These observations are consistent with the predictions of the theoretical model of Buraschi, Trojani, and Vedolin (2011). Therefore, we conclude

that large cross-market deviations are observed for firms that are more likely to be subject to high uncertainty/differences of opinion.

We now proceed with the discussion of our explanations for the specific pattern of the predictability of unusually large cross-market deviations that we document. Our analysis suggests that after the occurrence of large cross-market deviations, equity (both option and cash) markets move in line with the predictions of prior movements of the CDS market. Stocks in the low portfolio for example, exhibit negative returns which are consistent with the path of CDS prior to the occurrence of large (negative) cross-market deviations (Figure 2, Panel A). Negative stock returns however are not to be expected after decreases in put prices which are observed for these firms prior to the event.

We believe there are two potential explanations for this phenomenon. First, the CDS contract might be generally more 'informed' than the option contract and hence the equity option and the cash equity prices react with some delay to new information (e.g. Acharya and Johnson, 2007; Berndt and Ostrovnaya, 2008, Qiu and Yu, 2012). [26] Second, none of the two contracts is more 'informed' than the other, but a point might come at which the cross-market deviations are perceived as sufficiently large to trigger capital structure arbitrage activity (e.g. Duarte, Longstaff, and Yu, 2007; Yu, 2006). One potential form of the capital structure arbitrage strategy requires that CDS are bought (sold) and hedged with either short (long) positions in puts or long (short) positions in the underlying equity. We stress that these two explanations are not necessarily mutually exclusive.

Figure 2, Panel A, indicates that post the observation of a large negative cross-market deviation (after CDS become unusually more expensive than put options) the CDS remains relatively unchanged; put option prices increase and (in contrast to the options related literature) equity prices decrease rapidly. These observations are consistent with 'informed' trading in the CDS market and subsequent adjustment of prices in the equity markets. In addition, in Table 4 we observe that the CDS of firms in the 'Low Portfolio' exhibit the

[26] This explanation is consistent with the use of non-public information by informed traders that has recently been studied in different contexts, like syndicated loan agreements (Bushman, Smith, and Wittenberg-Moerman, 2010, Massoud et al., 2011), analysts' forecasts (Chen and Martin, 2011), and loan renegotiations (Ivashina and Sun, 2011).

highest liquidity, although the difference with the liquidity of CDS in the other portfolios is not extremely large. This observation provides additional support to our interpretation in light of the conclusion in Qiu and Yu (2012) that more CDS liquidity is associated with more information flow from the CDS to the equity market. Finally, when we compute the number of instances that firms experience downgrades (unreported analysis), we find that firms in the 'Low Portfolio' experience more downgrades in the six-month period after their inclusion than firms in the other portfolios do. This is an ex-post confirmation that trading in the CDS market is likely to have been 'informed'. We cannot completely rule out that capital structure arbitrage may also contribute to the predictability of cross-market deviations for firms in the 'Low Portfolio'. However, that CDS remain relatively unchanged on average after the event makes us reluctant to infer that the CDS is subsequently traded aggressively by capital structure arbitrage traders. To sum up, the predictability of negative cross-market deviations can either be explained with the 'informed' trading or the capital structure arbitrage trading hypotheses, although the former caters for a more likely explanation.

The results in Panel B demonstrate that post the observation of a large positive cross-market deviation (after the put option becomes unusually more expensive than the CDS), the CDS increases; put option prices decrease and (in contrast to the options related literature) equity prices increase rapidly. The explanation that 'informed' trading in CDS markets drives the results we document is consistent with our findings for the firms in the 'High Portfolio' too. However, the explanation that capital structure arbitrage activity contributes to the pattern of prices we observe in this instance becomes more relevant and the 'informed' trading explanation less dominant for a number of reasons. First, we observe that both CDS and option prices change after large deviations occur, which suggests that the demand for buying both contracts increases. Notably, changes in the respective URCs are almost of the same magnitude. Second, the bid-ask spreads for CDS and equity options we observe at the event are less consistent with the predictions of microstructure models in relation to informed trading. For example low (in relative terms) bid-ask spreads in options are not consistent with the predictions of Easley, O'Hara, and Srinivas (1998) pooling equilibrium; high (in relative terms) bid-ask spreads in CDS are not reconciled with the model of endogenous liquidity provision of Boulatov and George (2011). Third, our (unreported) analysis suggests that firms in the 'High Portfolio' experience downgrades less often than firms in the 'Low

Portfolio' (although more often than firms in the mid portfolio) which is consistent with the CDS being less likely to be 'informed'. Collectively, the predictability of positive cross-market deviations can either be explained with the 'informed' trading or the capital structure arbitrage trading hypotheses. Our evidence is not sufficient to favour one explanation over the other.

# 8 Conclusion

Cross-market information flow is a subject of widespread interest. The vast majority of the current studies focus on cross-market information flow between two securities only. We argue that this literature neglects that information may flow between more than two securities of the same firm. Studying the linkages of all potentially related securities of the same firm has important implications on the inferences regarding future prices of these securities.

In this study we focus on three securities of the same firm: a credit default swap on a firm's debt, an option on its equity, and the equity of the firm. Our starting point is the link between deep out of the money put options and credit default swaps developed in CW. We study cross-market information flow by means of the impact of large deviations of deep out of the money put options and credit default swaps from their fair, relative valuations, on equity valuations. We find that these deviations are economically and statistically significant, robust, predictors of future equity returns. The predictability we document is an integral, thus far unattended, component of the predictability of cross-market deviations documented in previous work.

A possible explanation for this finding is that the CDS contract is more 'informed' than the option contract. One other not mutually exclusive explanation is that when CDS and option prices largely deviate from their expected relative levels, portfolio managers engaging in capital structure arbitrage initiate trades that drive CDS, equity option, and equity prices back to their normal levels. The first explanation seems to sufficiently reconcile the predictability of cross-market deviations when CDS are unusually more expensive that put options. While the first explanation also possibly reconciles the predictability of cross-market deviations when put options are unusually more expensive that CDS, the capital structure arbitrage explanation we provide caters for a reasonable alternative.

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## Figures and Tables

**Figure 1: Abnormal cross-market deviations in unit recovery claim values over different reference dates**

The solid blue line plots the median excess difference at each reference date between the spread in unit recovery claim values estimated from the American put market ($UR^P$) and that from the CDS market ($UR^C$) and their historical rolling mean. The two dash-dotted lines represent the 25th- and 75th-percentiles.

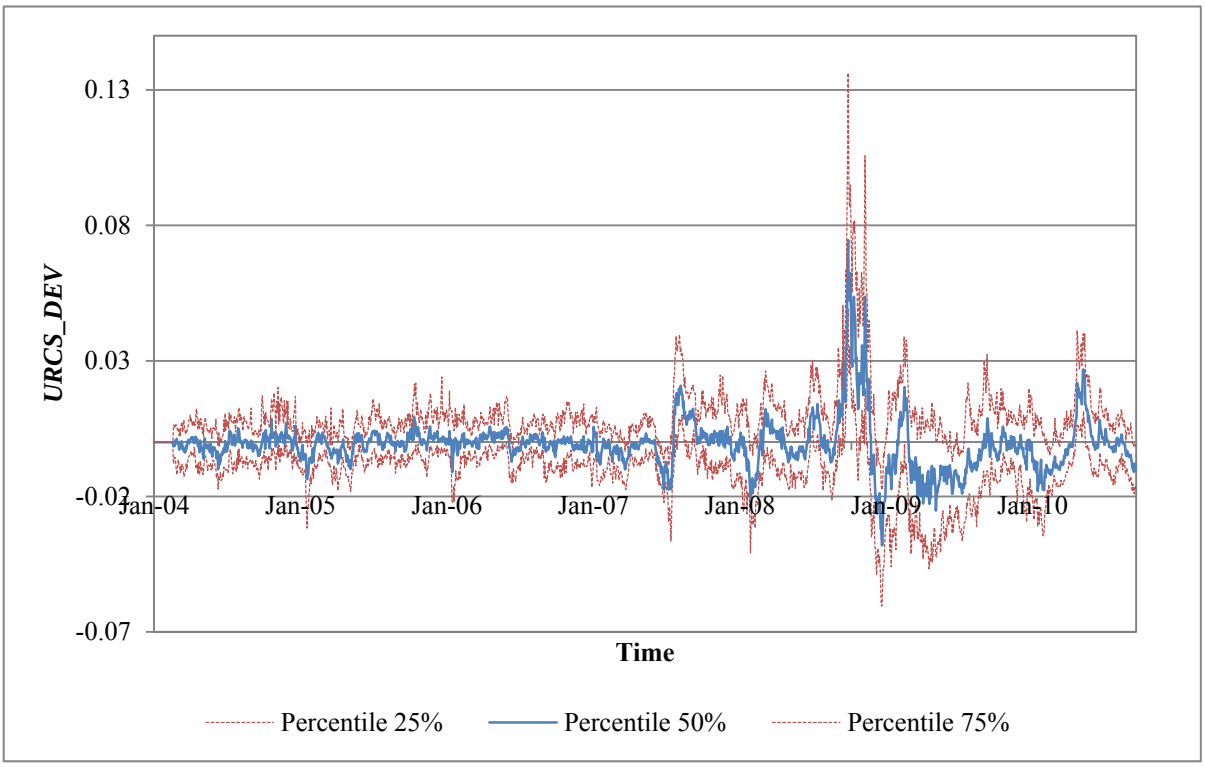
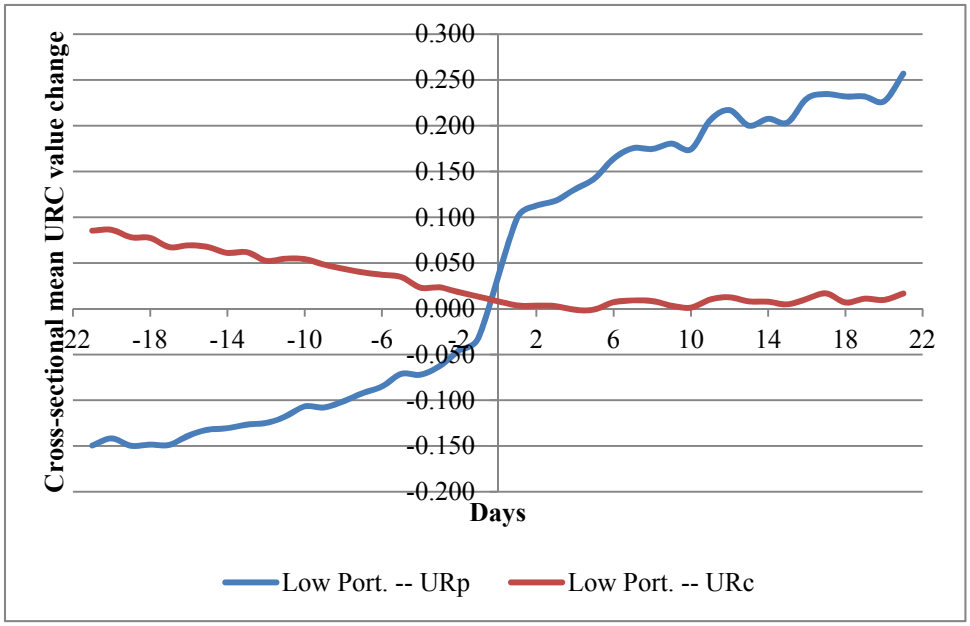


**Figure 2: Pre- and post-event unit recovery claim value changes**

An event is defined as a cross-market deviation of the difference in the unit recovery claim values from its expected value. The event-date is set at time 0 and a time window of -21 days to +21 days is studied (x-axis). Changes in unit recovery claim values are measured on the y-axis.

**Panel A: Unit recovery claim value changes for large negative cross-market deviations, i.e.**

$\left((UR_t^p - UR_t^c) - mean(UR^p - UR^c)\right) < 0$




**Panel B: Unit recovery claim value changes for large positive cross-market deviations, i.e.**

$\left((UR_t^p - UR_t^c) - mean(UR^p - UR^c)\right) > 0$

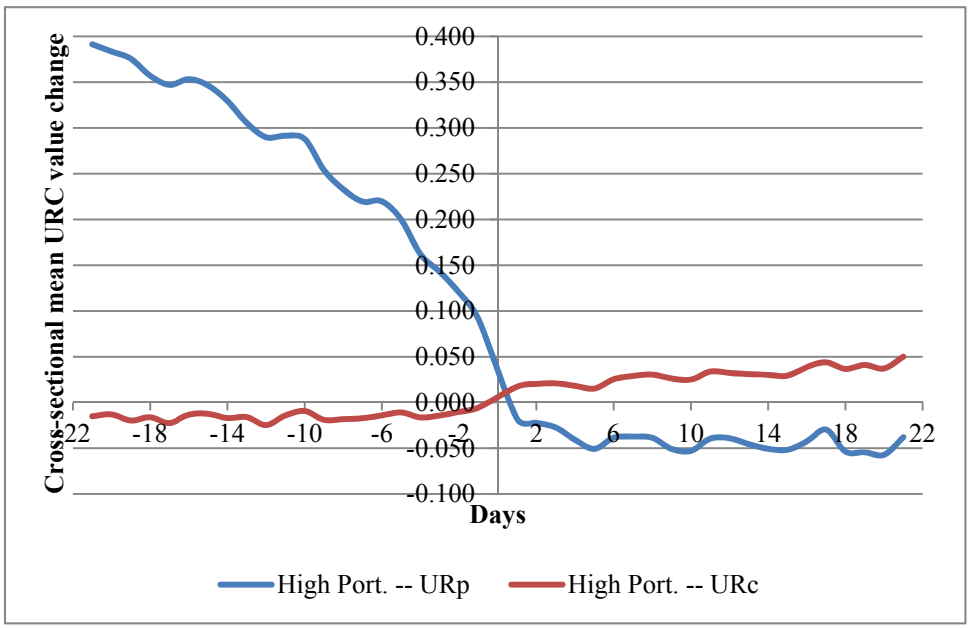
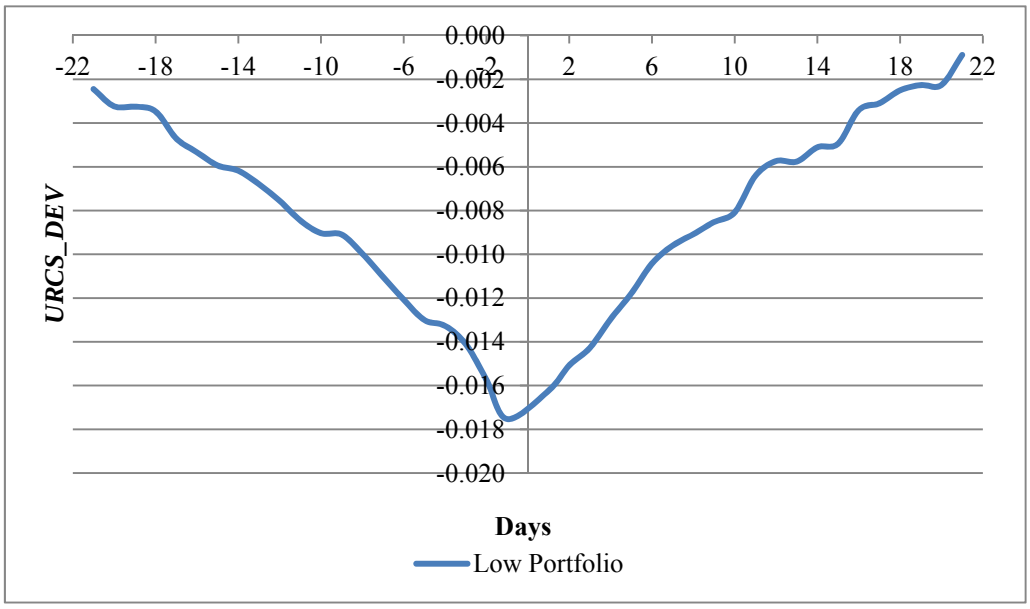


**Figure 3: Pre- and post-event cross-market deviation from expected values**

An event is defined as a cross-market deviation of the difference in the unit recovery claim values from its expected value. The event-date is set at time 0 and a time window of -21 days to +21 days is studied (x-axis). Deviations from expected values are measured on the y-axis.

**Panel A: Large negative cross-market deviations, i.e.** $\left((UR_t^p - UR_t^c) - mean(UR^p - UR^c)\right) < 0$




**Panel B: Large positive cross-market deviations, i.e.** $\left((UR_t^p - UR_t^c) - mean(UR^p - UR^c)\right) > 0$

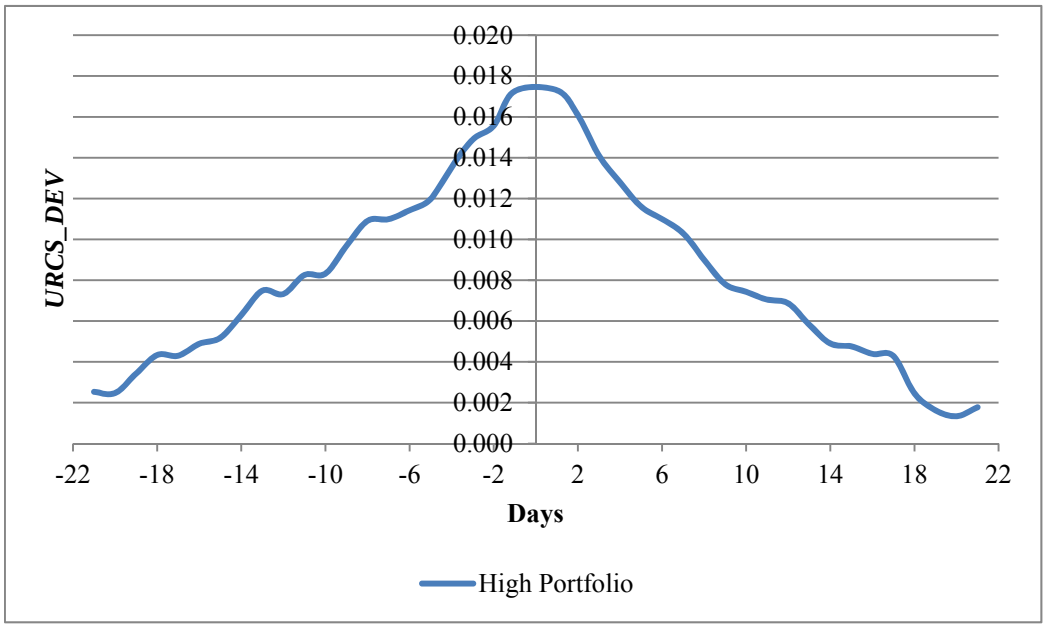


**Figure 4: Long/Short (cash) equity strategy returns**

This graph shows the wealth curves of 1 dollar invested in the hedge portfolio which is formulated weekly on the basis of the firms' *URCS_DEV* (H-L), in the low (L-M) and high (H-M) *URCS_DEV* portfolio in excess of the market, and in the market (M) for the period March 2004 to September 2010.

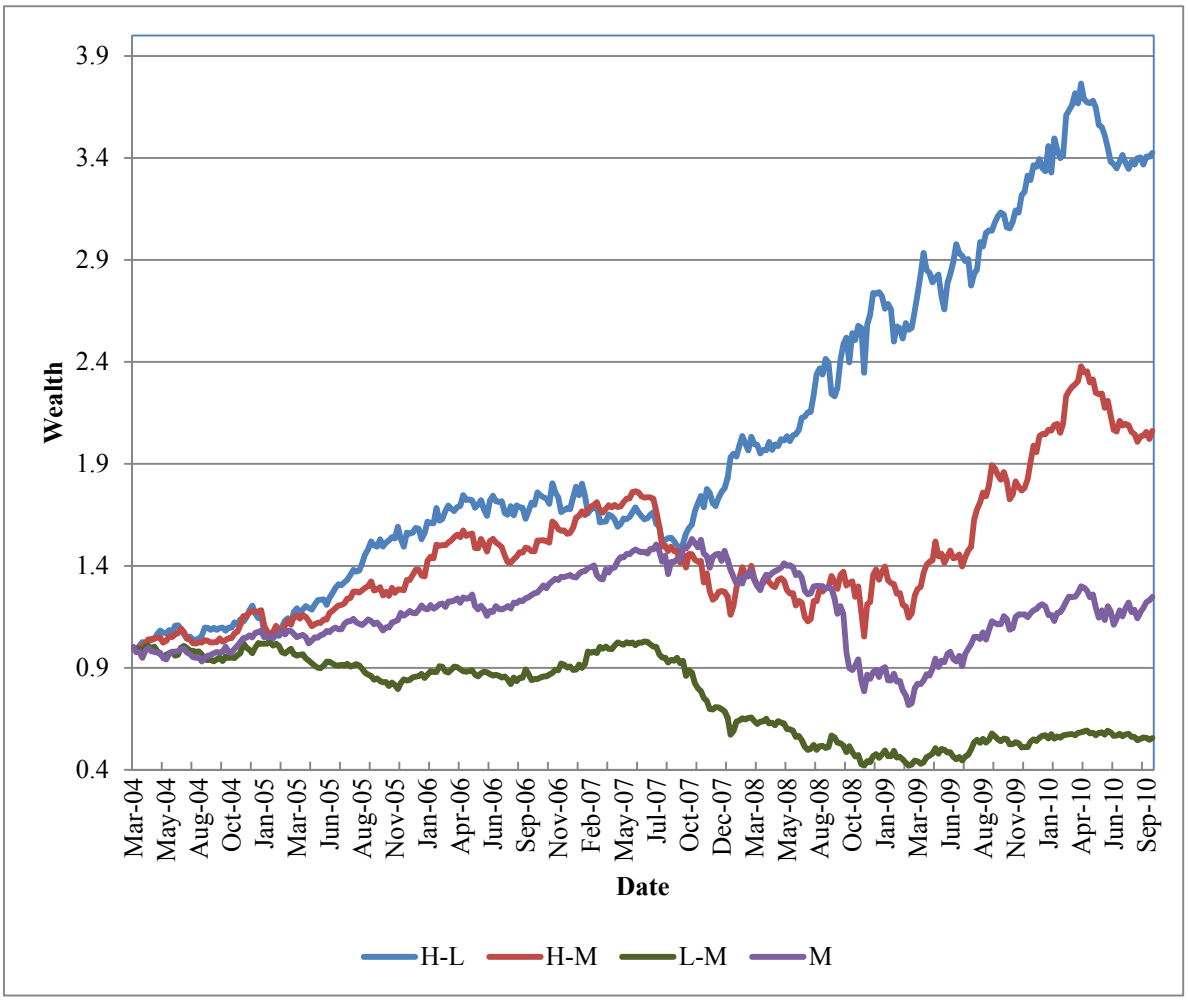


**Table 1: Sample descriptive statistics**

This table provides information for the firms, the firms' options contracts, and the firms' CDS contracts. Data are sourced from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Panel A reports the sample firms' characteristics which include the market capitalization in billion $ (SIZE), the book value of debt in billion $ (DEBT), the total debt over the book value of equity (TD/BE), the total debt over the market value of equity (TD/MC), the fraction of the total shares outstanding traded on a given day (TURNOVER), and idiosyncratic volatility (IDIOVOL) obtained after adjusting daily firm excess returns for market risk, size and value premiums, and momentum over a one-month period as in Ang et al. (2006). Panel B reports the sample firms' options contracts characteristics which include the options moneyness (K/S), the deep out of the money put options implied volatilities ($IV^P$), the interpolated one year 50-delta put option implied volatility ($ATMV^P$), and the deep out of the money put options open interest (OI). Panel C reports the sample firms' CDS contracts characteristics which include the mid CDS spread in basis points (CDS), and the firms' credit rating (CREDIT RATING). We also report the number of firms (No) in each industry group.

| **Panel A: Firm characteristics** | | | **Panel B: Equity option characteristics** | | | **Panel C: Credit and CDS characteristics** | | |
|---|---|---|---|---|---|---|---|---|
| SIZE | 10% | 1.39 | K/S | 10% | 0.322 | CDS | 10% | 133.00 |
| | Median | 4.90 | | Median | 0.523 | | Median | 256.00 |
| | 90% | 19.71 | | 90% | 0.657 | | 90% | 707.11 |
| DEBT | | | | | | CREDIT | | |
| | 10% | 0.97 | $IV^P$ | 10% | 0.361 | RATING | 10% | B |
| | Median | 3.36 | | Median | 0.563 | | Median | BB |
| | 90% | 17.14 | | 90% | 0.942 | | 90% | BBB+ |
| BM | 10% | 0.18 | $ATMV^P$ | 10% | 0.273 | | | |
| | Median | 0.64 | | Median | 0.430 | | | |
| | 90% | 1.52 | | 90% | 0.715 | | | |
| TD/BE | 10% | 0.29 | OI | 10% | 35 | | | |
| | Median | 0.97 | | Median | 674 | | | |
| | 90% | 4.99 | | 90% | 13370 | | | |
| TD/MC | 10% | 0.23 | | | | | | |
| | Median | 0.78 | | | | | | |
| | 90% | 3.02 | | | | | | |
| TURNOVER | 10% | 0.51% | | | | | | |
| | Median | 1.43% | | | | | | |
| | 90% | 4.24% | | | | | | |
| IDIOVOL | 10% | 0.145 | | | | | | |
| | Median | 0.273 | | | | | | |
| | 90% | 0.569 | | | | | | |

**Table 2: Future Market Movements Based on Current Cross-Market Deviations of Unit Recovery Estimates**

The results in this table refer to a two-stage procedure. In the first stage we define $D_t = (UR_t^p - UR_t^c)$ and regress it on various company, option, CDS, and liquidity characteristics $(X_t)$ that is:

$$D_t = a + bX_t + \delta_t$$

This analysis uses daily data over the past two-month period to calculate the residual $\delta_t$. In the second stage the regression residual $\delta_t$ is used to predict future unit recovery claim value movements, as follows:

$$UR_{t+\Delta t}^p - UR_t^p = \alpha^p + \beta^p \delta_t + e_{t+\Delta t}$$

and

$$UR_{t+\Delta t}^c - UR_t^c = \alpha^c + \beta^c \delta_t + \eta_{t+\Delta t}$$

The table reports $\overline{R^2}$ which is the average value of the *R-squares* from the first regression, estimates of $\beta^p$ and $\beta^c$ from the second-stage pooled regressions and the *R-squares* from the second-stage pooled regressions. The superscripts *p* and *c* denote the information source as the put option contract on a firm's equity and the CDS written on the corporate bond of a firm respectively. We consider two forecasting horizons: Δt = 1 week and Δt = 4 weeks. The top row refers to the case where $X_t = 1$, that is when the cross-market deviations is just demeaned by its average value over the past two-month period. The characteristics $X_t$ include a proxy for the average level of URC value $(UR^p + UR^c)/2$, the Black and Scholes (1973) delta of the put option in absolute magnitude |*DELTA*|, the DOOM put option moneyness ln*(K/S)* and implied volatility $IV^p$, the interpolated one year 50-delta put option implied volatility $ATMV^p$, 30- and 360-business-day realized variance of the option underlying equity $RV^{30}$ *and* $RV^{360}$ respectively, the total debt over the market value of equity (*TD/MC*), a default-probability measure *DF* estimated based on the structural model of Merton (1974) using total debt, one-year at-the-money option implied volatility, and market capitalization, the Amihud's (2002) equity illiquidity measure *ILLIQ,* the CDS bid-ask spread ($ILLIQ^{CDS}$) as an illiquidity measure for the CDS market, and the option premium bid-ask spread ($ILLIQ^p$) as an illiquidity measure for the options market. The last row reports results for using all illiquidity measures (equity, CDS, and options market) in a multiple variable regression.

| | | **Δt = 1 week** | | | | | | **Δt = 4 weeks** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\overline{R^2}$ | $\beta^p$ | | $R^2$ | $\beta^c$ | | $R^2$ | $\beta^p$ | | $R^2$ | $\beta^c$ | | $R^2$ |
| 1 | 0.00% | -0.225 | (0.007) | 5.60% | 0.048 | (0.005) | 0.54% | -0.349 | (0.011) | 5.33% | 0.073 | (0.009) | 0.42% |
| $(UR^p + UR^c)/2$ | 51.06% | -0.235 | (0.010) | 2.71% | 0.076 | (0.007) | 0.59% | -0.334 | (0.017) | 2.17% | 0.116 | (0.013) | 0.47% |
| **\|DELTA\|** | 59.48% | -0.135 | (0.010) | 0.95% | 0.078 | (0.007) | 0.66% | -0.218 | (0.017) | 0.96% | 0.112 | (0.013) | 0.46% |
| **ln(K/S)** | 50.04% | -0.141 | (0.010) | 1.10% | 0.073 | (0.007) | 0.61% | -0.240 | (0.016) | 1.24% | 0.089 | (0.012) | 0.30% |
| **$IV^p$** | 35.17% | -0.247 | (0.009) | 3.82% | 0.058 | (0.006) | 0.43% | -0.323 | (0.015) | 2.56% | 0.102 | (0.011) | 0.45% |
| **$ATMIV^p$** | 29.43% | -0.335 | (0.009) | 6.82% | 0.059 | (0.006) | 0.44% | -0.454 | (0.015) | 4.88% | 0.084 | (0.012) | 0.30% |
| **$RV^{30}$** | 22.11% | -0.261 | (0.009) | 4.87% | 0.072 | (0.006) | 0.77% | -0.353 | (0.015) | 3.47% | 0.109 | (0.011) | 0.58% |
| **$RV^{360}$** | 25.84% | -0.274 | (0.009) | 4.73% | 0.088 | (0.007) | 1.01% | -0.308 | (0.016) | 2.33% | 0.103 | (0.012) | 0.46% |
| **TD/MC** | 29.88% | -0.280 | (0.009) | 5.19% | 0.071 | (0.006) | 0.69% | -0.372 | (0.015) | 3.54% | 0.083 | (0.012) | 0.31% |
| **DF** | 14.16% | -0.227 | (0.010) | 4.27% | 0.048 | (0.008) | 0.35% | -0.257 | (0.017) | 2.20% | 0.089 | (0.014) | 0.40% |
| **ILLIQ** | 4.85% | -0.247 | (0.007) | 5.81% | 0.050 | (0.005) | 0.50% | -0.374 | (0.012) | 5.24% | 0.070 | (0.009) | 0.32% |
| **$ILLIQ^{CDS}$** | 11.32% | -0.249 | (0.007) | 5.52% | 0.054 | (0.005) | 0.55% | -0.392 | (0.013) | 5.39% | 0.060 | (0.010) | 0.22% |
| **$ILLIQ^p$** | 28.02% | -0.204 | (0.009) | 3.05% | 0.063 | (0.006) | 0.65% | -0.320 | (0.015) | 2.93% | 0.069 | (0.011) | 0.25% |
| **ILLIQ, $ILLIQ^{CDS}$, $ILLIQ^p$** | 39.30% | -0.223 | (0.010) | 2.88% | 0.071 | (0.007) | 0.65% | -0.360 | (0.017) | 2.95% | 0.056 | (0.013) | 0.13% |

**Table 3: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps after Controlling for Other Effects (Fama and McBeth, 1973)**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two-month period for each firm, *URCS_DEV*. We normalize this variable. Ln(SIZE) is the logged firm market capitalization. BM is the book-to-market ratio. MOM is the previous 1-month return. SKEW is the skewness factor constructed as in Chang, Christoffersen, and Jacobs (2010). ILLIQ is the Amihud's (2002) equity illiquidity measure. We report Fama-MacBeth (1973) regression estimates for weekly returns, as specified in equation (7), along with t-statistics obtained with Newey-West (1987) adjustment. Three sets of regression estimates are reported. First, estimates from a straight regression of firm returns against their previous week respective normalized *URCS_DEV* value (specification [1]). Second, estimates from a regression of firm returns against their previous week respective normalized *URCS_DEV* value and additional predictive variables for size and value premiums, and momentum (specification [2]). Third, estimates from a regression of firm returns against their previous week respective normalized *URCS_DEV* value and additional predictive variables for size and value premiums, momentum, Chang, Christoffersen, and Jacobs (2010) skewness measure, and Amihud's (2002) illiquidity measure (specification [3]).

| | [1] | [2] | [3] |
|---|---|---|---|
| **Constant** | 0.0011 | 0.0256 | 0.0168 |
| ***t-stat*** | 0.48 | 1.49 | 0.78 |
| ***URCS_DEV*** | 0.0024 | 0.0020 | 0.0017 |
| ***t-stat*** | 3.71 | 3.20 | 2.93 |
| **Ln(SIZE)** | - | -0.0012 | -0.0008 |
| ***t-stat*** | - | -1.63 | -0.85 |
| **BM** | - | -0.0005 | 0.0001 |
| ***t-stat*** | - | -0.41 | 0.05 |
| **MOM** | - | 0.0079 | 0.0061 |
| ***t-stat*** | - | 1.07 | 0.84 |
| **SKEW** | - | - | -0.0377 |
| ***t-stat*** | - | - | -0.88 |
| **ILLIQ** | - | - | 1.5801 |
| ***t-stat*** | - | - | 0.74 |
| **Adj $R^2$** | 1.90% | 9.60% | 12.71% |

**Table 4: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps, Portfolio Forming Approach – Portfolio Descriptive Statistics**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm. We sort stocks in tercile portfolios. *URCS_DEV* is the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months. SIZE is the firm market capitalization. BM is the book-to-market ratio. MOM is the previous 1-month return. SKEW is the skewness measure constructed as in Chang, Christoffersen, and Jacobs (2010). ILLIQ is the Amihud's (2002) illiquidity measure. $IV^p$ is the DOOM put option implied volatility. $ILLIQ^p$ is the option premium bid-ask spread as a percentage of the mid-spread. CDS is the CDS spread of the reference entity, and $ILLIQ^{CDS}$ is the CDS bid-ask spread as a percentage of the mid-spread. Panel A reports the time-series average value of each portfolios constituent firms' cross-sectional averages. Panel B reports the time-series averages of the cross-sectional correlations of all the variables.

**Panel A: Mean characteristic values**

| | Factor | SIZE | BM | MOM | SKEW | $10^6$xILLIQ | $IV^p$ | $ILLIQ^p$ | CDS | $ILLIQ^{CDS}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Low Portfolio** | -0.021 | 7.592 | 0.716 | 0.027 | 0.000 | 0.495 | 0.599 | 0.489 | 413.149 | 0.061 |
| **2** | -0.001 | 8.426 | 0.669 | 0.011 | -0.001 | 0.406 | 0.538 | 0.448 | 289.023 | 0.063 |
| **High Portfolio** | 0.021 | 7.524 | 0.704 | 0.000 | -0.001 | 0.522 | 0.595 | 0.334 | 390.269 | 0.064 |

**Panel B: Average correlations**

| | Factor | SIZE | BM | MOM | SKEW | $10^6$xILLIQ | $IV^p$ | $ILLIQ^p$ | CDS | $ILLIQ^{CDS}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| ***URCS_DEV*** | 1 | -0.016 | -0.004 | -0.059 | -0.026 | 0.016 | -0.006 | -0.204 | -0.036 | 0.036 |
| **SIZE** | | 1 | -0.082 | 0.004 | 0.015 | -0.244 | -0.265 | -0.013 | -0.277 | -0.115 |
| **BM** | | | 1 | 0.010 | -0.011 | 0.227 | 0.058 | 0.026 | 0.013 | -0.042 |
| **MOM** | | | | 1 | -0.023 | 0.002 | -0.017 | 0.046 | 0.007 | 0.031 |
| **SKEW** | | | | | 1 | -0.019 | 0.021 | -0.009 | 0.019 | -0.008 |
| **ILLIQ** | | | | | | 1 | 0.333 | 0.096 | 0.344 | 0.045 |
| **$IV^p$** | | | | | | | 1 | -0.111 | 0.672 | -0.055 |
| **$ILLIQ^p$** | | | | | | | | 1 | -0.096 | -0.008 |
| **CDS** | | | | | | | | | 1 | -0.008 |
| **$ILLIQ^{CDS}$** | | | | | | | | | | 1 |

**Table 5: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps, Portfolio Forming Approach**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio.

| | EX RET | ALPHA | MARKET | SIZE | VALUE | MOM | SKEW | SR | No |
|---|---|---|---|---|---|---|---|---|---|
| **Low Portfolio** | -0.088% | -0.217% | 1.326 | 0.576 | 0.625 | -0.002 | 0.108 | -0.070 | 20.01 |
| **2** | -0.029% | -0.130% | 1.295 | 0.344 | 0.318 | 0.006 | -0.081 | 0.027 | 19.97 |
| **High Portfolio** | 0.318% | 0.145% | 1.276 | 0.594 | 0.677 | -0.241 | 0.167 | 0.549 | 20.01 |
| **High – Low** | 0.406% | 0.363% | -0.050 | 0.017 | 0.052 | -0.239 | 0.059 | 1.333 | 40.02 |
| ***t-stat*** | 3.42 | 3.39 | -0.91 | 0.14 | 0.52 | -3.43 | 0.36 | - | - |

**Table 6: Decay of the Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps, Portfolio Forming Approach**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio. Panel A, B, C, and D report average returns, regression estimates, and firm characteristics for portfolios rebalanced after one, two, three, and four weeks after the initial portfolio formation respectively.

| | **EX RET** | **ALPHA** | **MARKET** | **SIZE** | **VALUE** | **MOM** | **SKEW** | **SR** | **No** |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Week 1 | | | | | | | | | |
| **Low Portfolio** | -0.088% | -0.217% | 1.326 | 0.576 | 0.625 | -0.002 | 0.108 | -0.070 | 20.01 |
| **2** | -0.029% | -0.130% | 1.295 | 0.344 | 0.318 | 0.006 | -0.081 | 0.027 | 19.97 |
| **High Portfolio** | 0.318% | 0.145% | 1.276 | 0.594 | 0.677 | -0.241 | 0.167 | 0.549 | 20.01 |
| **High – Low** | 0.406% | 0.363% | -0.050 | 0.017 | 0.052 | -0.239 | 0.059 | 1.333 | 40.02 |
| ***t-stat*** | 3.42 | 3.39 | -0.91 | 0.14 | 0.52 | -3.43 | 0.36 | - | - |
| Panel B: Week 2 | | | | | | | | | |
| **Low Portfolio** | 0.072% | -0.076% | 1.288 | 0.585 | 0.668 | -0.055 | 0.297 | 0.181 | 19.98 |
| **2** | 0.026% | -0.098% | 1.243 | 0.411 | 0.365 | -0.058 | 0.003 | 0.125 | 19.94 |
| **High Portfolio** | 0.133% | -0.053% | 1.388 | 0.563 | 0.604 | -0.235 | -0.101 | 0.254 | 19.98 |
| **High – Low** | 0.061% | 0.023% | 0.100 | -0.022 | -0.064 | -0.180 | -0.398 | 0.187 | 39.96 |
| ***t-stat*** | 0.48 | 0.20 | 1.21 | -0.13 | -0.45 | -2.70 | -2.29 | - | - |
| Panel C: Week 3 | | | | | | | | | |
| **Low Portfolio** | 0.149% | -0.004% | 1.255 | 0.627 | 0.802 | -0.042 | 0.126 | 0.299 | 19.95 |
| **2** | 0.057% | -0.071% | 1.265 | 0.268 | 0.306 | -0.119 | -0.066 | 0.179 | 19.91 |
| **High Portfolio** | 0.020% | -0.168% | 1.402 | 0.595 | 0.536 | -0.270 | 0.068 | 0.091 | 19.95 |
| **High – Low** | -0.129% | -0.164% | 0.147 | -0.032 | -0.266 | -0.228 | -0.058 | -0.404 | 39.91 |
| ***t-stat*** | -1.03 | -1.56 | 2.18 | -0.23 | -2.52 | -1.96 | -0.28 | - | - |
| Panel D: Week 4 | | | | | | | | | |
| **Low Portfolio** | 0.144% | -0.015% | 1.285 | 0.610 | 0.705 | -0.024 | -0.074 | 0.294 | 19.92 |
| **2** | -0.027% | -0.175% | 1.308 | 0.329 | 0.289 | -0.143 | 0.020 | 0.028 | 19.89 |
| **High Portfolio** | 0.172% | -0.039% | 1.366 | 0.530 | 0.625 | -0.318 | 0.055 | 0.305 | 19.92 |
| **High – Low** | 0.028% | -0.023% | 0.081 | -0.080 | -0.080 | -0.294 | 0.129 | 0.084 | 39.85 |
| ***t-stat*** | 0.21 | -0.20 | 1.03 | -0.58 | -0.55 | -2.09 | 0.57 | - | - |

**Table 7: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps for interpolated CDS, Portfolio Forming Approach**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio.

| | EX RET | ALPHA | MARKET | SIZE | VALUE | MOM | SKEW | SR | No |
|---|---|---|---|---|---|---|---|---|---|
| **Low Portfolio** | -0.154% | -0.334% | 1.330 | 0.904 | 0.694 | -0.185 | -0.092 | -0.143 | 11.60 |
| **2** | 0.066% | -0.081% | 1.313 | 0.665 | 0.454 | -0.095 | 0.048 | 0.158 | 11.64 |
| **High Portfolio** | 0.304% | 0.142% | 1.499 | 0.555 | 0.574 | -0.149 | 0.012 | 0.444 | 11.60 |
| **High – Low** | 0.458% | 0.476% | 0.170 | -0.349 | -0.120 | 0.037 | 0.104 | 0.847 | 23.21 |
| ***t-stat*** | 2.18 | 2.18 | 1.65 | -1.72 | -0.59 | 0.32 | 0.44 | - | - |

**Table 8: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps for positive Book Value firm, Portfolio Forming Approach**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio.

| | EX RET | ALPHA | MARKET | SIZE | VALUE | MOM | SKEW | SR | No |
|---|---|---|---|---|---|---|---|---|---|
| **Low Portfolio** | -0.104% | -0.234% | 1.312 | 0.598 | 0.632 | -0.004 | 0.070 | -0.094 | 19.01 |
| **2** | -0.034% | -0.135% | 1.289 | 0.325 | 0.339 | 0.009 | -0.069 | 0.017 | 19.00 |
| **High Portfolio** | 0.273% | 0.101% | 1.278 | 0.607 | 0.642 | -0.247 | 0.182 | 0.479 | 19.01 |
| **High – Low** | 0.376% | 0.334% | -0.034 | 0.009 | 0.010 | -0.244 | 0.111 | 1.207 | 38.03 |
| ***t-stat*** | 3.10 | 2.94 | -0.60 | 0.07 | 0.10 | -3.59 | 0.70 | - | - |

**Table 9: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps after Controlling for Other Effects (Fama and McBeth,1973) and Credit Rating**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two-month period for each firm, *URCS_DEV*. We normalize this variable. Ln(SIZE) is the logged firm market capitalization. BM is the book-to-market ratio. MOM is the previous 1-month return. SKEW is the skewness factor constructed as in Chang, Christoffersen, and Jacobs (2010). ILLIQ is the Amihud's (2002) equity illiquidity measure. We report Fama-MacBeth (1973) regression estimates for weekly returns, as specified in equation(7), along with t-statistics obtained with Newey-West (1987) adjustment. Three sets of regression estimates are reported. First, estimates from a straight regression of firm returns against their previous week respective normalized *URCS_DEV* value (specification [1]). Second, estimates from a regression of firm returns against their previous week respective normalized *URCS_DEV* value, a dummy variable which equals 1 if a company is classified as non-investment grade, which is rating below BBB, and an interaction variable between the dummy variable and the normalized *URCS_DEV* value (specification [2]). Third, estimates from a regression of firm returns against their previous week respective normalized *URCS_DEV* value, a dummy variable which equals 1 if a company is classified as non-investment grade, which is rating below BBB, and an interaction variable between the dummy variable and the normalized *URCS_DEV* value and additional predictive variables for size and value premiums, and momentum (specification [3]). Fourth, estimates from a regression of firm returns against their previous week respective normalized *URCS_DEV* value, a dummy variable which equals 1 if a company is classified as non-investment grade, which is rating below BBB, and an interaction variable between the dummy variable and the normalized *URCS_DEV* value and additional predictive variables for size and value premiums, momentum, Chang, Christoffersen, and Jacobs (2010) skewness measure, and Amihud's (2002) illiquidity measure (specification [4]).

| | [1] | [2] | [3] | [4] |
|---|---|---|---|---|
| **Constant** | 0.0010 | -0.0007 | 0.0415 | 0.0377 |
| ***t-stat*** | 1.71 | -0.64 | 2.75 | 2.26 |
| **D** | - | 0.0023 | -0.0001 | 0.0001 |
| ***t-stat*** | - | 1.81 | -0.04 | 0.05 |
| ***URCS_DEV*** | 0.0023 | 0.0049 | 0.0061 | 0.0063 |
| ***t-stat*** | 4.01 | 4.17 | 4.66 | 4.79 |
| ***URCS_DEV* x D** | - | -0.0034 | -0.0046 | -0.0048 |
| ***t-stat*** | - | -2.56 | -3.13 | -3.26 |
| **Ln(SIZE)** | - | - | -0.0018 | -0.0017 |
| ***t-stat*** | - | - | -2.83 | -2.33 |
| **BM** | - | - | 0.0004 | 0.0003 |
| ***t-stat*** | - | - | 0.62 | 0.40 |
| **MOM** | - | - | 0.0043 | 0.0044 |
| ***t-stat*** | - | - | 1.17 | 1.20 |
| **SKEW** | - | - | - | -0.0634 |
| ***t-stat*** | - | - | - | -3.15 |
| **ILLIQ** | - | - | - | 0.3332 |
| **t-stat** | - | - | - | 0.51 |
| **Adj $R^2$** | 0.07% | 0.11% | 0.17% | 0.21% |

**Table 10: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps after controlling for each component's factor returns, Portfolio Forming Approach**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. $URCS_DEV^c$ (Panel A) is the estimated loading on returns of a long/short strategy based on the difference of CDS unit recovery claim value from its previous two-month average value, and $URCS_DEV^p$ (Panel B) is the estimated loading on returns of a long/short strategy based on the difference of DOOM put option unit recovery claim value from its previous two-month average value. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio.

| | **EX RET** | **ALPHA** | **MARKET** | **SIZE** | **VALUE** | **MOM** | **SKEW** | **URCS_DEV$^c$** | **SR** | **No** |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: | | | | | | | | | | |
| **Low Portfolio** | -0.088% | -0.128% | 1.164 | 0.353 | 0.217 | 0.126 | -0.191 | 0.163 | -0.070 | 20.01 |
| **2** | -0.029% | -0.109% | 1.025 | 0.307 | 0.221 | 0.036 | -0.123 | -0.026 | 0.027 | 19.97 |
| **High Portfolio** | 0.318% | 0.186% | 0.998 | 0.427 | 0.396 | -0.161 | -0.237 | -0.041 | 0.549 | 20.01 |
| **High – Low** | 0.406% | 0.314% | -0.166 | 0.074 | 0.179 | -0.287 | -0.046 | -0.204 | 1.333 | 40.02 |
| ***t-stat*** | 3.42 | 2.93 | -2.59 | 0.66 | 1.68 | -3.87 | -1.01 | -3.48 | - | - |
| | **EX RET** | **ALPHA** | **MARKET** | **SIZE** | **VALUE** | **MOM** | **SKEW** | **URCS_DEV$^p$** | **SR** | **No** |
| Panel B: | | | | | | | | | | |
| **Low Portfolio** | -0.088% | -0.165% | 1.124 | 0.331 | 0.282 | 0.035 | -0.217 | -0.089 | -0.070 | 20.01 |
| **2** | -0.029% | -0.106% | 1.045 | 0.306 | 0.199 | 0.080 | -0.116 | 0.091 | 0.027 | 19.97 |
| **High Portfolio** | 0.318% | 0.181% | 1.061 | 0.415 | 0.333 | -0.021 | -0.219 | 0.327 | 0.549 | 20.01 |
| **Low – High** | 0.406% | 0.345% | -0.063 | 0.085 | 0.050 | -0.056 | -0.002 | 0.417 | 1.333 | 40.02 |
| ***t-stat*** | 3.42 | 4.08 | -1.53 | 0.81 | 0.62 | -1.07 | -0.05 | 7.59 | - | - |

**Table 11: Predictability of Cross-Market Deviations in Equity Options and Credit Default Swaps, Portfolio Forming Approach in subsamples**

This table sources data from CRSP and Compustat (for stocks), OptionMetrics (for options), and CMA (for CDS). Our sample period is January 2004 to September 2010. Every Wednesday we compute the deviation of the difference ($UR^p$-$UR^c$) and its mean value over the previous two months for each firm, *URCS_DEV*. We sort stocks with based on *URCS_DEV* in tercile portfolios. EXRET is the weekly excess return over the risk-free rate. ALPHA is the weekly risk-adjusted return. MARKET, SIZE, VALUE, MOM, and SKEW are estimated loadings on the market, size, value premiums, momentum, and skewness premiums respectively. SR is the annualized Sharpe Ratio. No is the average number of firms in each portfolio. Results are reported for two sub-periods. For January 2005 to July 2007. For August 2007 to September 2010. For the latter period we also report results after excluding the period of the Global Financial Crisis (GFC), in particular the weeks of short-selling ban (This period is from July 21, 2008 to August 12, 2008, and from September 19, 2008 to October 8, 2008).

| | EX RET | ALPHA | MARKET | SIZE | VALUE | MOM | SKEW | SR | No |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: January 2005 – July 2007** | | | | | | | | | |
| **Low Portfolio** | 0.161% | -0.058% | 1.294 | 0.532 | 0.168 | -0.007 | -0.229 | 0.647 | 12.44 |
| **2** | 0.146% | -0.054% | 1.258 | 0.234 | 0.087 | 0.112 | -0.297 | 0.696 | 12.38 |
| **High Portfolio** | 0.450% | 0.237% | 1.238 | 0.700 | 0.117 | -0.163 | -0.055 | 1.424 | 12.44 |
| **High – Low** | 0.289% | 0.295% | -0.056 | 0.168 | -0.051 | -0.156 | 0.175 | 0.995 | 24.87 |
| ***t-stat*** | 1.84 | 2.20 | -0.41 | 0.71 | -0.29 | -0.78 | 0.47 | - | - |
| **Panel B: August 2007 – September 2010** | | | | | | | | | |
| **Low Portfolio** | -0.325% | -0.307% | 1.300 | 0.599 | 0.715 | -0.001 | 0.191 | -0.360 | 28.16 |
| **2** | -0.182% | -0.163% | 1.290 | 0.412 | 0.343 | 0.004 | -0.019 | -0.220 | 28.13 |
| **High Portfolio** | 0.222% | 0.160% | 1.231 | 0.521 | 0.813 | -0.247 | 0.220 | 0.279 | 28.16 |
| **High – Low** | 0.547% | 0.466% | -0.069 | -0.078 | 0.098 | -0.246 | 0.029 | 1.719 | 56.32 |
| ***t-stat*** | 3.06 | 2.77 | -0.99 | -0.50 | 0.77 | -3.18 | 0.15 | - | - |
| **Panel C: August 2007 – September 2010 (ex-GFC)** | | | | | | | | | |
| **Low Portfolio** | -0.141% | -0.302% | 1.320 | 0.552 | 0.720 | -0.013 | 0.171 | -0.148 | 28.11 |
| **2** | 0.014% | -0.128% | 1.284 | 0.384 | 0.359 | 0.006 | -0.018 | 0.049 | 28.09 |
| **High Portfolio** | 0.350% | 0.075% | 1.294 | 0.527 | 0.766 | -0.282 | 0.175 | 0.435 | 28.11 |
| **High – Low** | 0.490% | 0.378% | -0.026 | -0.025 | 0.045 | -0.268 | 0.003 | 1.552 | 56.23 |
| ***t-stat*** | 2.72 | 2.38 | -0.32 | -0.17 | 0.35 | -4.13 | 0.02 | - | - |