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Abstract

This paper studies variance risk premiums in the credit market. Using a novel data set of swaptions quotes on the CDX North America Investment Grade index, we find that returns of credit variance swaps are negative and economically large. Shorting variance swaps yields an annualized Sharpe ratio of almost six, eclipsing its counterpart in fixed income or equity markets. The returns remain highly statistically significant when accounting for transaction costs, cannot be explained by established risk-factors, and hold for various investment horizons. We also dissect the overall variance risk premium into payer and receiver variance risk premiums. We find that exposure to both parts is priced. However, the returns for payer variance, associated with bad economic states, are roughly twice as high in absolute terms.

JEL classification: G12, G13.

Keywords: Variance risk premium, CDS implied volatility, CDS variance swap

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1. Introduction

The analysis of variance risk and its associated market price has gained a lot of interest over the last one and a half decades. It has become standard to use the notion of variance swaps to assess the sign, significance and magnitude of variance risk premiums. In a variance swap, the ex-post realized variance is exchanged for a fixed variance swap rate, set at swap inception. The difference in the swap rate and the ex-post realized variance constitutes the variance risk premium.

Variance risk premiums have been studied extensively for a broad range of asset classes. To the best of our knowledge, we are the first academic study to conduct this kind of analysis in credit markets. Thereby, we draw upon a new data set of options written on the CDX North America Investment Grade 5 Year Index, one of the most prominent corporate credit indices in the world. Based on the work of Neuberger (1994), Demeterfi, Derman, Kamal, and Zou (1999) and Britten-Jones and Neuberger (2000), and in line with previous studies, we synthetically construct the variance swap rate from out-of-the-money payer and receiver swaptions. Since variance swaps are set up to have zero value at inception, the swap rate constitutes the ex ante risk neutral expecation of realized variance. In order to be agnostic about the stochastic process of the underlying Credit Default Swap (CDS, hereafter) spread, we define realized variance along the lines of Neuberger (2012) in a generalized version. More precisely, we only require the process for the CDS spread to be a martingale and explicitly allow for jumps. Additionally, our estimates are free of discretization biases. These characteristics have made the framework of Neuberger (2012) the prevailing choice for realized variance in the recent literature (see Trolle and Schwartz, 2014; Choi, Mueller, and Vedolin, 2017; Kaeck, 2018). Contrarily, defining realized variance by means of squared log returns leaves the variance risk premiums exposed to cubed returns (see Carr and Wu, 2009).

Insights from equity (Carr and Wu, 2009), foreign exchange (Ammann and Buesser, 2013), interest rate (Trolle and Schwartz, 2014), Treasury bond (Choi et al., 2017), commodity (Trolle and Schwartz, 2010; Prokopczuk, Symeonidis, and Wese Simen, 2017), and variance-of-variance (Kaeck, 2018) markets point towards strongly negative variance risk premiums. Credit markets are fundamentally different from other asset classes. In the case of equity markets, negative variance risk premiums have been associated with the desire of investors to protect themselves against economically unfavourable states of the world. They are willing to pay a premium for holding assets paying off in bad states of the economy.[1] CDS provide

[1]Dew-Becker, Giglio, Le, and Rodriguez (2017) show that a model with time-variation in exposure to disasters is able to explain the main characteristics of the equity variance term structure.

protection in case firms default on their outstanding debt. The latter happens frequently in economic downturns. Hence, by their very nature, CDS yield similar characteristics as variance risk premiums. CDS spreads differ also in another dimension from equity, foreign exchange or fixed income markets, namely with respect to their statistical properties. Log changes in CDS spreads exhibit a high degree of positive skewness and kurtosis (see Byström (2006) for European corporate sector indices). In case of US single-name CDS, Oh and Patton (2018) document an average excess kurtosis of above 25. For 5% of firms in their sample, log-differences of daily CDS spreads exhibit excess kurtosis above 75. Further evidence on high kurtosis is provided by Byström (2007). He studies tail-properties of the main European corporate credit index by means of margin calculations in a hypothetical credit default swap index futures markets. He finds that the use of extreme value theory is superior to traditional margin calculations based on the normal distribution. Hence, it is not a-priori clear, if credit markets exhibit also negative variance risk premiums.

Although the credit default swap market has undergone tremendous changes in the last years,[2] particular investor interest in volatility-related credit derivatives has been documented very recently. Peterseil (2019) reports the introduction of an exchange traded fund exposed to credit variance risk by selling at-the-money straddles on European and US sub-investment grade credit indices.[3] Furthermore, it has been reported that investment banks have launched a credit equivalent of the VIX index in response to growing investor demand (Bartholomew, 2017).

In line with other asset classes, we find large and significant variance risk premiums in credit markets. More precisely, an investment strategy capturing credit variance risk premiums (CVP, hereafter) by means of shorting 1-month variance swaps yields average monthly excess returns of 42%. The associated Sharpe ratio is close to six. Thereby, CVP eclipses its counterpart of nearly all other asset classes by a large margin. Moreover, CVP is highly statistically significantly different from zero with a t-statistic of 14 in absolute terms. We compare CVP, measured by the difference in ex ante risk-neutral implied and ex post realized variance, to another popular trading strategy exposed to variance risk, namely, investing in an at-the-money (ATM) straddle. The 1-month ATM straddle generates a return of only of half of CVP, underpinning the large returns of shorting pure credit variance.

In order to shed light on the sources of CVP, we focus on corridor variance risk premiums. In light of Andersen and Bondarenko (2010) and Kaeck (2018), we decompose CVP into

[2]See Aldasoro and Ehlers (2018) and references therein for an excellent overview.

[3]Selling at-the-money straddles is an alternative option strategy for volatility exposure. Choi et al. (2017) argue that this exposure is, however, non-linear. Furthermore, selling straddles leaves exposure to other factors. The authors document significantly smaller returns from selling straddles compared to variance swaps.

payer and receiver variance risk premiums with the help of corridor variance swaps. In the latter, price moves of the underlying constitute only to realized variance if they happen to be within a specific price corridor. Payer (receiver) variance risk premiums are associated with price moves of the CDS spread above (below) the CDS spread observed at swap inception. Therefore, payer variance risk premiums are associated with bad economic states, receiver variance risk premiums with good states. We find that both semi-variance risk premiums are significantly different from zero and sizeable. However, 1-month payer variance risk premiums are nearly twice as large as receiver variance risk premiums (in absolute terms), amounting to -51% on average.

Subsequently, we study whether CVP can be explained by common equity asset pricing risk factors. We find that the equity market return taken as sole potential driver of CVP is positive, but not significant. Extending the risk-factor space to the Fama-French six factor model (Fama and French, 2018) reveals that the equity market exhibits a negative sign, as expected, and the correlation becomes significant. Furthermore, CVP shows positively and negatively significant relationship to the size and investment portfolio, respectively. However, our analysis documents that CVP, and also semi-variance risk premiums, remain largely unexplained.

Next, we examine time variation in CVP in the style of Carr and Wu (2009). Our results suggest that risk premiums based in dollar terms are informative regarding future realized variance and exhibit time-variation. However, risk premiums defined via log returns appear to be more similar to a constant or independent time series. These findings are in line with Carr and Wu (2009) for equity markets.

Motivated by the literature on linking credit with equity markets, we study the comovement of CVP with equity variance risk premiums and equity variance-of-variance risk premiums. We furthermore include fixed-income variance risk premium, as previous literature has documented that single corporate CDS spreads are partly driven by interest rates (Ericsson, Jacobs, and Oviedo, 2009). CVP loads significantly and positively on variance-of-variance risk premiums. However, the latter are not sufficient to fully explain the former.

Finally, we challenge our findings with two robustness checks. First, we also vary the investment horizon of variance swap contracts. CVP remain highly attractive considering investment periods of up to 4 months, yielding returns around -46%. The same holds true for payer and receiver variance risk premiums. Whereas the former monotonically increase in absolute terms in the investment horizon, the latter monotonically decline. Second, we analyze the impact of bid and ask spreads on the profitability of credit variance swaps. Its importance is illustrated by Driessen, Maenhout, and Vilkov (2009). Once controlling for transaction costs, the authors find that correlation risk premiums lose their attractiveness over equity risk premiums. In our case, however, shorting variance remains highly attractive after transaction costs. We document highly significant average returns of 20%, putting CVP approximately on par with Treasury bond variance risk premiums before transaction costs.

Our paper is related to various strands in the literature. First and foremost, it draws upon the vast literature on documenting variance risk premiums across different asset classes. Carr and Wu (2009) has been the first to document negative and economically large variance risk premiums. Whereas the authors concentrate on equity markets, Ammann and Buesser (2013) adopt the approach and study foreign exchange variance risk premiums. Trolle and Schwartz (2010) and Prokopczuk et al. (2017) analyze commodity markets, and Trolle and Schwartz (2014) and Choi et al. (2017) focus on fixed income. Instead of constructing variance swap rates synthetically from a continuum of option prices, Egloff, Leippold, and Wu (2010) obtain over-the-counter variance swaps and study their term structure. Filipović, Gourier, and Mancini (2016) resort also to over-the-counter variance swaps to motivate a quadratic term structure model for equity variance swaps.

Moreover, our analysis produces credit implied volatility indices as by-products. Equity implied volatilities have gained prominent space in the academic literature, and practice. The VIX, computed from options on the S&P 500, is known as the fear gauge due to its tendency to increase in times of negative equity market returns. Carr and Wu (2006) estimate an instantaneous correlation effect between S&P 500 returns and changes in the VIX of -0.78. Whaley (2009) documents that the VIX reacts asymmetrically to changes in the S&P 500. The change in VIX rises at a higher rate when the stock market is falling than if it is rising. Mele, Obayashi, and Shalen (2015) extend the analysis to the interest rate swap market. The authors establish stylized facts of SRVX, the swap rate volatility index, constructed similarly to VIX, based on interest rate swaptions. Moreover, they compare the SRVX to VIX and find different behavior beteween both. Attention has been also paid to the term structure of implied volatilities. Ait-Sahalia, Karaman, and Mancini (2018) show that in case of equities it is upward sloping. Its counterpart in Treasury bond markets is, however, downward sloping and its slope exhibits predictive power for economic growth and economic stress, as reported by Choi et al. (2017). Johnson (2017) document that the slope of the VIX term structure carries information about S&P 500 variance risk and predicts variance swap, VIX futures, and S&P 500 straddle returns.

Another strand of literature is concerned with risk premiums and trading strategies in credit markets. Longstaff, Pan, Pedersen, and Singleton (2011) use the affine sovereign credit model of Pan and Singleton (2008) to dissect sovereign credit default spreads into their risk premiums and a default risk component. They find a significant risk premium amounting to one third of the CDS spread. Moreover, both components are strongly related to global macroeconomic factors. However, the link is more pronounced for the default risk component. Jarrow, Li, Ye, and Hu (2019) explore mispricings in the term structure of CDS spreads. The latter use a reduced-form credit risk model to construct out of sample market-neutral portfolios along the term structure of corporate CDS. The documented mispricings tend to be positively related to market volatility and credit and liquidity risk factors.

Finally, we contribute to the substantial literature linking credit derivatives to equity markets. The theoretical motivation for most studies is the structural model of Merton (1974). In his model, a firm's default probability is depending on the firm's leverage, equity volatility, and the level of the risk-free rate. Different measures for equity volatility have been employed in the literature. Collin-Dufresne, Goldstein, and Martin (2001) employ the VIX index as a substitute of firms implied volatilities of traded options. On the contrary, Campbell and Taksler (2003) and Ericsson et al. (2009) use realized volatility. The latter authors find that realized volatility and leverage carry substantial explanatory power in explaining levels and changes of corporate CDS spreads. Cremers, Driessen, Maenhout, and Weinbaum (2008) incorporate implied alongside realized volatility in their regression model. Focusing on CDS levels, they document an improved estimation fit when including implied volatilities from firms' individual options. Cao, Yu, and Zhong (2010) refine the use of option implied information. As the authors argue, CDS exhibit similar features to out-of-the-money put options as both offer effective protection against downside risks. They find that firms' put option-implied volatility is superior to historical volatility. On the one hand, the authors relate their finding to the ability of implied volatility to predict future realized volatility. On the other hand, they find that volatility risk premium in option prices co-moves with CDS spreads. Another strand of research has looked at lead-lag-relationships between equity and credit markets. Norden and Weber (2009) document that equity returns are leading CDS spreads, whereas the opposite does not hold true. Moreover, CDS are more sensitive to the stock market than to bond markets. Hilscher, Pollet, and Wilson (2015) confirm these findings in a more recent sample period.

The remainder of the paper is structured as follows. Section 2 details our methodological framework. In section 3, we present our data set. Section 4 describes and discusses our main empirical findings, whereas section 5 concludes.

2. Methodology

2.1. Credit Default Index Swaptions

A credit default swap (CDS) is a contract giving its holder the right to sell a bond for its face value in case of default or otherwise specified credit event by the bond issuer. Consequently, a CDS index (CDIS) tracks the cost of buying protection for each company in a portfolio. A buyer of protection on a CDIS receives insurance against losses stemming from defaults of any of the index's single-name constituents during the lifetime of the contract. In exchange, the protection buyer pays a fixed coupon and a cash upfront payment to the protection seller at trade inception.

In the following, we use the notation of Rutkowski (2012). Let $T_0 < T_1 < \cdots < T_m$ denote the tenor structure of a forward-start CDIS, where

- $T_0 = T$ is the inception date,
- T_m is the maturity date,
- T_j is the jth fee payment date for $j = 1, \dots, m$.

We further assume that the recovery rate $\delta \in [0, 1]$ is predetermined, constant and the same for all reference entities in the CDIS. More generally, we assume that firms are identical. We denote by B the process for the money-market account which is assumed to be strictly positive. Let n be the initial number of reference entities and τ_i the time at which entity i defaults, then $J_t = n - \sum_{i=1}^{n} \mathbb{1}_{\{t \geq \tau_i\}} = \sum_{i=1}^{n} \mathbb{1}_{\{\tau_i > t\}}$ denotes the number of entities which have survived up to time t.

We will later consider options written on a forward CDIS with expiry $T = T_0$. Their pricing will be based on a change of numéraire argument. For the remainder, we assume that the event $\{\tau_n \leq T\}$ has zero probability under $\mathbb{Q}$. This ensures that the candidate numéraire is strictly positive and does not vanish with non-zero probability. Economically, the technicality rules out the default of all reference entities before swaption maturity.[4]

From the perspective of the CDIS seller, the value of the forward CDIS with spread κ at time $t \in [0, T_0]$ is

$$S_t^n(\kappa) = \mathbb{E}_t^{\mathbb{Q}}(P_t^n) - \kappa \mathbb{E}_t^{\mathbb{Q}}(A_t^n),$$

[4] Morini and Brigo (2011) refer to the default of all entities as the *Armageddon event*, whereas Rutkowski (2012) uses the term *collapse event*. The authors have shown that incorporating the event requires knowledge of the risk-neutral conditional distribution of τ_n. Rutkowski (2012) is silent on its estimation, while Morini and Brigo (2011) resort to index tranches.

where

$$
\begin{aligned}
P_t^n =&(1-\delta) B_t \sum_{i=1}^{m} B_{\tau_i}^{-1} \mathbb{1}_{\{T_0<\tau_i\leq T_m\}} \\
A_t^n =&B_t \sum_{j=1}^{m} \alpha_j B_{T_j}^{-1} J_{T_j},
\end{aligned}
$$

with $\alpha_j = T_j - T_{j-1}$ for every $j = 2, \ldots, m$ and $\mathbb{E}_t^{\mathbb{Q}}$ denotes the risk-neutral expectation given the information available up to time t. P_t^n is the discounted payoff of the protection leg, whereas A_t^n is the discounted payoff of the fee leg per one unit of the spread.[5] The latter is also known as risky annuity or defaultable price value of the basis point. It is market convention to compute the implied risk-neutral probabilities for different maturities using a flat single-name CDS curve with a constant spread equalling κ_t^n. Therefore, we can approximate A_t^n by $J_t PV_t \kappa_t^n$, where $PV_t \kappa_t^n$ is the risky annuity calibrated by a flat CDS curve with spread equalling the actually quoted CDIS spread in the market.

An option on a CDIS, also referred to as a swaption, is an agreement to sell or buy protection on the underlying index with a certain maturity at a pre-agreed spread. Swaptions are European options. The option holder of a payer index option has the right, but no obligation, to buy protection in the index at the strike spread. On the contrary, a receiver option entitles its holder the right to sell protection in the index at the strike spread.

Assume that the CDIS was initiated at time 0, with constant spread κ_0^n. κ_T^n denotes the prevailing market spread at time T. $\mathcal{P}_T(t, \kappa)$ represents the time-t value of a European payer swaption with maturity $T = T_0$ and strike spread κ. At expiration, the swaption has a payoff of

$$
\left(PV_T(\kappa_T^n) J_T(\kappa_T^n - \kappa_0^n) - nPV_T(\kappa)(\kappa - \kappa_0^n) + L_T\right)^+, \tag{1}
$$

where $L_t = (1-\delta)\sum_{i=1}^{n} \mathbb{1}_{\{\tau_i \leq t\}}$ denotes the loss process of the CDIS. We would like to point out several noteworthy aspects with respect to Equation (1). First, unlike forward CDIS, swaptions provide protection from losses occurring between option inception and option maturity T. Secondly, $PV_T(\kappa)$ denotes the risky annuity at time T and hence is random in the interest rates. On the contrary, $PV_T(\kappa_T)$ is random in interest rates and the index spread κ_T. We follow market convention and approximate future interest rates by current forward rates for the same date. Consequently, randomness in $PV_T(\kappa)$ vanishes and $PV_T(\kappa_U)$ remains to be random with respect to κ_T only. We can rewrite the swaption payoff in Equation (1)

[5] We suppress the dependence of A_t^n on the inception date of the forward-start CDIS, $T_0 = T$, for ease of notation.

to

$$\left(S_T^n(\kappa) + L_T\right)^+ = \left(S_T^a(\kappa)\right)^+, \tag{2}$$

where $S_T^a(\kappa) = S_T^n(\kappa) + L_T$ denotes the loss-adjusted forward CDIS and we have used the approximation $PV_T(\kappa)n \approx PV_T(\kappa_T)J_T \approx A_T^n$. The price of the loss-adjusted forward CDIS at time $t \in [0, T]$ is given by

$$S_t^a(\kappa) = \mathbb{E}_t^{\mathbb{Q}}(P_t^a) - \kappa \mathbb{E}_t^{\mathbb{Q}}(A_t^n),$$

where $P_t^a = P_t^n + B_t B_T^{-1} L_T$. Consequently, the loss-adjusted fair forward CDIS spread at any time $t \in [0, T]$ is the random variable $\kappa_{t,T}^a$ which solves $S_t^a(\kappa_{t,T}^a) = 0$. For every $t \in [0, T]$,

$$\kappa_{t,T}^a = \frac{\mathbb{E}_t^{\mathbb{Q}}(P_t^a)}{\mathbb{E}_t^{\mathbb{Q}}(A_t^n)},$$

and the price of the forward CDIS can be expressed as, for every $t \in [0, T]$

$$S_t^a(\kappa_t^a) = A_t^a(\kappa_{t,T}^a - \kappa). \tag{3}$$

By inspection of Equations (2) and (3), we see that through a suitable change of numéraire,[6] the price of a payer option is given as

$$\mathcal{P}_T(t, \kappa) = A_t^a \mathbb{E}_t^{\mathbb{A}}\left[(\kappa_{t,T}^a - \kappa)^+\right], \tag{4}$$

where $\mathbb{A}$ denotes the risky annuity measure associated with A_t^a as numéraire. The corresponding receiver swaption, denoted by $\mathcal{R}_T(t, \kappa)$, has a time-t price of

$$\mathcal{R}_T(t, \kappa) = A_t^a \mathbb{E}_t^{\mathbb{A}}\left[(\kappa - \kappa_{t,T}^a)^+\right]. \tag{5}$$

Equations (4) and (5) illustrate that a payer swaption can be associated with a call option on the CDIS spread, whereas a receiver swaption resembles the notion of a put option.

2.2. Variance Swap Contracts

This subsection introduces variance swaps in credit markets. In a variance swap, the long side receives the difference between the realized variance of the CDIS spread over the life of

[6] See Rutkowski (2012) for details.

the contract and a pre-determined rate K

$$(RV_{t,T} - K) \times A_t^a, \tag{6}$$

where $RV_{t,T}$ denotes the realized variance of $\kappa_{t,T}^a$ over a partition $\Pi = \{t = t_0 < \dots\ t_n = T\}$ of the interval from t to T and is defined as

$$RV_{t,T} = 2 \times \left[\left(\frac{\kappa_{t_1,T}^a}{\kappa_{t_0,T}^a} - 1 - \log \frac{\kappa_{t_1,T}^a}{\kappa_{t_0,T}^a} \right) + \dots + \left(\frac{\kappa_{t_n,T}^a}{\kappa_{t_{n-1},T}^a} - 1 - \log \frac{\kappa_{t_n,T}^a}{\kappa_{t_{n-1},T}^a} \right) \right]. \tag{7}$$

The definition in Equation (7) is based on Neuberger (2012) and Bondarenko (2014) and has been adopted frequently in the recent literature (see Choi et al., 2017; Kaeck, 2018).[7] The popularity of realized variance as in Equation (7) stems from two facts. First, its risk-neutral expectation can be calculated in a model-free way if $\kappa_{t,T}^a$ follows a martingale, and hence, the latter is not restricted to be a continuous process. Second, results are robust to discretization biases. The inclusion of the risky annuity in Equation (6) is adapted from Mele and Obayashi (2015).

The fixed variance swap rate is determined as the value for K such that the variance swap has zero value at t, it solves

$$\mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^T r(s)ds} (RV_{t,T} - K) \times A_t^a \right] = 0,$$

and is given by

$$K \equiv IV_{t,T} = \mathbb{E}_t^{\mathbb{Q}} \left[RV_{t,T} \right] = \frac{2}{A_t^a} \int_0^\infty \frac{\mathcal{M}_T(t,\kappa)}{\kappa^2} d\kappa, \tag{8}$$

where

$$\mathcal{M}_T(t,\kappa) = \begin{cases} \mathcal{R}_T(t,\kappa) & \text{if } \kappa \le \kappa_t^a \\ \mathcal{P}_T(t,\kappa) & \text{if } \kappa > \kappa_t^a \end{cases} \tag{9}$$

To shed further light on the sources of credit variance risk premiums, we follow the ideas of Andersen and Bondarenko (2010) and Kaeck (2018) and decompose (implied and realized) return variation into price ranges by means of corridor variances.[8] Generally, corridor variance is constructed as

$$IV_{t,T}^{B_u,B_d} = \frac{2}{A_t^a} \int_{B_d}^{B_u} \frac{\mathcal{M}_T(t,\kappa)}{\kappa^2} d\kappa, \tag{10}$$

[7] Trolle and Schwartz (2014) use a similar approach based on arithmetic changes, whereas Equation (7) is a generalized version of log-changes.

[8] The concept was initially introduced by Carr and Madan (1998).

where $\mathcal{M}_T(t,\kappa)$ as in Equation (9), and B_d (B_u) denotes the lower (upper) bound of the price corridor. The realized counterpart is given as

$$RV_{t,T}^{B_u,B_d} = \sum_{i=1}^{n} g(\kappa^a_{t_i,T}) - g(\kappa^a_{t_{i-1},T}) - g'(\kappa^a_{t_{i-1},T}) \cdot \left(\kappa^a_{t_i,T} - \kappa^a_{t_{i-1},T}\right), \tag{11}$$

where

$$g(x) = \begin{cases} 2 \times \left(-\log B_u - \frac{x}{B_u} + 1\right) & \text{if } x > B_u \\ -2 \times \log x & \text{if } x \in [B_d, B_u] \\ 2 \times \left(-\log B_d - \frac{x}{B_d} + 1\right) & \text{if } x < B_d \end{cases}$$

and $g'(x)$ denotes the derivative of g with respect to x. Model-invariance and robustness to discretization are retained by Equation (11) (see Bondarenko, 2014). We focus on the two most intuitive price ranges, namely upside and downside variances. Upside (downside) variance is the return variation when the current forward CDIS spread is above (below) the starting forward CDIS spread. More precisely, in the former case we have $B_d = 0$ and $B_u = \kappa^a_{t_0,T}$, whereas in the latter $B_d = \kappa^a_{t_0,T}$ and $B_u = \infty$. Since Equation (10) breaks into either payer or receiver swaptions, we term the semi-variances payer and receiver variances.

Equations (8) and (10) and require a continuum of option prices. However, only a finite number of strikes is available. We follow ideas from Carr and Wu (2009) to compute the integrals in Equations (8) and (10). First, we obtain and sort all out-of-the money swaptions for each date t and maturity T. Second, we construct a grid of implied volatilities at different moneyness levels. More precisely, we construct a grid of of 2000 implied volatility points within a strike range of ± 8 standard deviations from the current forward price. Thereby the standard deviation is approximated by the average implied volatility. Third, we linearly interpolate across moneyness. For strikes higher (lower) than the highest (lowest) listed strike price, we use the implied volatility at the highest (lowest) available strike. Finally, we convert the implied volatilities back into option prices using Black (1976).

3. Data

Credit swaptions data are obtained from Markit. Markit is considered the leading financial services and pricing data company in the area of credit default swaps. We focus on one of the most prominent North American credit indices, the CDX North America Investment Grade Index (CDX NA IG). CDX NA IG comprises 125 of the most liquid North American entities with investment grade credit rating. Markit is owner and administrator of the index. Along side the Markit iTraxx Europe Main, CDX NA IG is the globally main corporate credit derivative index based on traded volume (Augustin, Subrahmanyam, Tang, and Wang, 2014).

Credit swaptions are traded over-the-counter. Markit receives quotes on payer and receiver options from associated buy-side and sell-side accounts. After assuring data quality, Markit provides composite payer and receiver quotes per option maturity and strike. The composite quotes are formed by averaging the latest quotes over the tightest time window possible on each day ensuring a sufficient amount of quotes.

The data are available at a daily frequency from March 2012 to September 2018. The maturity date is the third Wednesday of each month. Data span the on-the-run series[9] and the first-off-the-run series of the 5 year indices. After the financial crisis of 2007-09, five-year contracts have become standard and make up the predominant portion in the market (see Abad, Aldasoro, Aymanns, D'Errico, Fache Rousová, Hoffmann, Langfield, Neychev, and Roukny, 2016). Data for the underlying reference indices are also provided by Markit.

From our data set, we keep only days where each of the four nearest maturities carry at least three strikes. We furthermore verify option implied forward spreads with their theoretical value using the ISDA CDS standard model.[10] Our filters leave us with 226872 receiver and payer swaptions.

The swaption data set for the CDX NA IG are described in Table 1. For each day, we group the available receiver and payer quotes into different maturity buckets, each spanning 30 days. Table 1 describes for each bucket the number of days with observed quotes, the average and median of the time to maturity, moneyness levels, and number of strikes. Besides showing statistics for the entire data set, Table 1 further differentiates between on-the-run and off-the-run series. There is considerably less data on the market for off-the-run series in any dimension considered. After applying our filter, we observe option quotes on off-the-run series only on a very few days. Furthermore, the number of strikes and the strike range is lower than in on-the-run series for longer maturities by a large margin. Within on-the-run series, the market for options with time to maturity between 30 and 120 days seems to be most liquid. Across all maturity buckets, we observe on average on any given day at least 9 different strikes. Though this seems to be little as compared to equity markets, it is noteworthy, that first studies on variance risk premiums on single stocks report number of strikes well below our numbers (see Carr and Wu, 2009).

In order to compare credit variance risk premiums with equity variance and equity variance-of-variance risk premiums, we obtain data on S&P 500, VIX index and the ex-

[9] The CDX NA IG index rolls every six months, i.e. a new index is issued. The new issue is known under an incremented series. The new series of the index is termed on-the-run index until a new series is created at the next roll date. It then becomes the first off-the-run index.

[10] We have implemented the ISDA CDS standard model according to White (2013).

change traded fund TLT options from OptionMetrics. The sample period spans the start of our swaptions data set until December 2017 (the most recent sample period available to us as of writing). The options are European-style in case of S&P 500 and VIX and written on the spot indices. Options on TLT are American-style and we use Barone-Adesi and Whaley (1987) to convert them to European options. For every day in our sample, we use put-call parity for the ATM option pair for which put and call prices are closest and back out implied forward prices.

4. Empirical results

4.1. Preliminary Data Analysis

We start by analysing annualized implied volatility of CDX NA IG (CIV, hereafter), defined as $\sqrt{(T-t)IV_{t,T}}$. We proceed as follows to construct these measures for constant maturities of 45, 75, and 105 days. At each day in our sample, we straddle the time to maturity of interest and compute implied variances for the neighbouring maturities. Subsequently, we interpolate linearly in implied variance to obtain a value at a fixed time to maturity.[11] In principle, this technique can be applied to any number of days. We have chosen 45 days as the shortest time to maturity instead of 30 days out of two reasons. First, we thereby avoid extrapolation as we observe for some days in our sample swaptions with maturities strictly above 30 days. Secondly, we disregard options with less than 7 days to maturity in the calculation of CIV. We do not consider time to maturities beyond 105 days since they are less actively traded.

[Insert Figure 1 near here]

Figure 1 displays CIV for the three time to maturities. First, all three time series exhibit strong time-variation. The lowest levels in all CIV indices are attained around mid-2017 after a period of slow, but gradually decline. At this point in time, CIV for 45 days is around 35%. Maximums in CIV levels are reached at several periods in our sample, where they reach roughly 70%. Secondly, we observe several noteworthy spikes. The most extreme appear to be around the US taper tantrum in 2013 and the "implosion" of inverse equity volatility products in early 2018. During both periods, CIV levels across all maturities nearly double within a few days. Thirdly, the term structure of implied volatility is most of the time upward sloping. This is best illustrated between mid-2016 and mid-2017. During periods of

[11]Precisely, denote by T_1 and T_2 the straddling maturities of T such that $T_1 < T < T_2$. Then implied variance for maturity T is given as $IV_{t,T} = \frac{1}{T-t}\left[\frac{IV_{t,T_1}(T_1-t)(T_2-t)+IV_{t,T_2}(T_2-t)(T_1-1)}{T_2-T_1}\right]$.

high stress, however, the term structure inverts. We observe this pattern particularly around spikes in CIV, for example, during the US taper tantrum in 2013. Fourthly and finally, the steepness of the term structure is a function of market calmness: the more quiet the market, the steeper the term structure, as seen during the first half of 2017.

[Insert Table 2 near here]

Table 2 presents summary statistics for the three different CIV indices. The unconditional means of CIV levels reflect the on-average upward sloping term structure. This is in line with equity implied volatility, as Ait-Sahalia et al. (2018) document strictly increasing mean levels of equity volatility swap rates. However, it does not manifest in implied equity volatility-of-volatility (Kaeck, 2018) or Treasury bond implied volatility (Choi et al., 2017), where mean levels are monotonically decreasing in time to maturity. It is noteworthy that the steepness of the term structure of unconditional implied volatilities is gentle. The difference in mean levels for 45 and 105 days amounts to roughly 2%, given that the average 45 day implied volatility reads 47.4%. Trolle and Schwartz (2014) observe a similar finding in USD and EUR denominated interest rate swaptions. Table 2 also confirms our visually inspection with respect to behavior of credit implied volatility during calm and stressful market periods. The minimum level of implied volatility is strictly increasing in time to maturity, whereas the opposite holds true for the maximum. This points towards the inversion of the term structure during times of market distress. The reduction in standard deviation for longer maturities adds to that point. Moreover, we observe that all CIV indices exhibit positive skewness and kurtosis, albeit monotonically declining in time to maturity.

In addition to levels, Table 2 shows statistics for log-changes in CIV indices. Our previous findings for CIV levels apply also to log-changes. We furthermore perform a principal component analysis of log-changes in the three CIV indices, reported in Table 3. Columns (2)-(4) display the loadings on our CIV indices. Similar to other term structures, the first principal component can be associated with a level factor, which accounts for nearly 96% of the variation in CIV indices. The second component represents a slope factor, covering roughly 3% of variation. The third component can be attributed to a curvature factor, accounting for roughly 1% of variation.

4.2. Credit variance risk premiums

After having established characteristics of CIV indices, we turn to credit variance risk premiums. We follow standard practice in the literature (Carr and Wu, 2009; Choi et al., 2017; Kaeck, 2018) and measure CVP via returns to credit variance swaps, where the returns are defined as $RV_{t,T}/IV_{t,T} - 1$.

[Insert Figure 2 near here]

An illustration of CVP is given in Figure 2. The figure depicts monthly realized variances of forward CDIS spreads next to their implied counterparts in the left graph. The corresponding returns are shown in the right graph. Each month the return is computed such that T corresponds to the expiry date of CDX NA IG index options in the next calendar month and t is the trading day succeeding the expiry date of the current month. Similar to variance swap investments in equity or fixed income markets, the realized variance is often well below its implied counterpart, leading to highly negative returns in most months. Realized variance outreaches implied variance during six months in our sample, leading to positive gains in a long variance swap.

[Insert Table 4 near here]

Table 4 summarizes the statistics for CVP. Shorting a credit variance swap yields a monthly average return of around 42%, which is highly significantly different from zero as given by the t-statistic of approximately 14. CVP eclipses its documented counterparts in most other asset classes. Kaeck (2018) estimates the equity variance-of-variance risk premium to amount to 24%. Choi et al. (2017) study Treasury variance swaps where they report monthly returns of around 20% for shorting Treasury variance. Trolle and Schwartz (2014) analyze interest rate variance swaps by means of EUR and USD dominated swaptions. They document mean monthly returns to shorting variance between 40% and 66%.

Another popular strategy for gaining exposure to volatility are ATM straddles. Coval and Shumway (2001) and Santa-Clara and Saretto (2009) document attractive Sharpe ratios above one for trading straddles on S&P 500 index futures. We synthetically construct ATM straddles with the same time to maturity as the variance swap. Results are also given in Table 4. Shorting ATM straddles yield average monthly returns of roughly 21%, statistically significantly different from zero. Therefore, the average returns are approximately half of the size of CVP . Furthermore, they appear also to be riskier, proxied by volatility.

[Insert Figure 3 near here]

To understand the variance risk premium in different states of the world, we study corridor variance swaps and their investment returns. We focus on payer- and receiver-corridors. The payer (receiver) corridor is determined by the prevailing forward CDIS spread at variance swap initiation as the lower (upper) bound. It is associated with rising (falling) CDIS spreads. Figure 3 depicts payer- and receiver-variances and corresponding risk premiums. Although payer- and receiver variance risk premiums are both leptokurtic and highly skewed, they exhibit notable differences. The realized payer variance equals zero for a considerable amount of months, especially during 2014 and 2017. We find only three of such occurrences for realized receiver variances. Furthermore, conditional on exceedance, realized receiver variance outreaches implied receiver variance by a wider margin. The visual inspection of payer and receiver variance risk premiums is confirmed in Table 4. Overall, both premiums earn highly negative and statistically significant returns, but findings are more pronounced for returns of payer variance swaps. The latter yields an average monthly return of -50% with a t-statistic of nearly -8. The average return for receiver variance swaps is -25% with a t-statistic of approximately -4.

Different implicit levels of leverage can distort the interpretation of monthly average returns. Therefore, we include risk-adjusted performance measures robust to leverage in Table 4: Sharpe ratio, Stutzer ratio, and Sortino ratio.[12] We adjust Sharpe ratios for return-autocorrelation when aggregating them to annualized numbers following Lo (2002). Not surprisingly, returns to credit variance swaps yield the highest Sharpe ratio in absolute terms. It amounts to nearly 6, four times higher than for selling ATM straddles. Sharpe ratios rest on the assumption of normality, however, CVP, as well as semi-variance risk premiums, exhibit positive skewness and excess kurtosis. Hence, the Stutzer ratio might be more suitable for comparing risk-adjusted performances. The findings in Table 4 confirm the high attractiveness of CVP from the perspective of the Stutzer ratio, where a similar margin to ATM straddles is observed. Since the standard deviations of payer and receiver variance risk premiums are nearly twice as high as for overall CVP, their Sharpe and Stutzer ratios are lower than for CVP. However, they are still well above their counterparts for ATM straddles.

To gain a sharper understanding of CVP, we put it into perspective of direct exposure to credit risk. We implement a short credit risk strategy by entering into a forward-starting CDX NA IG index, receiving the fixed leg and paying the floating leg in the underlying CDIS strategy. The payoffs to this strategy are fundamentally different from the return definition of credit variance swaps. The CVP is measured as a fully collaterialized long position in the variance swap posting $IV_{t,T}$ as collateral at initiation and receiving $RV_{t,T}$ plus interest at expiry. On the contrary, the payoff bearing direct credit risk is the profit or loss for a given, time-invariant notional investment in CDIS. In order to make the latter comparable to CVP, we introduce a required amount of capital needed to enter into a forward-CDIS. We adjust the amount such that the strategy generates the same unconditional volatility of

[12]The inclusion of these measures has been proposed by Bondarenko (2014) and adopted by Kaeck (2018), for example.

CVP.[13] Table 4 reports the results. The monthly average return amounts to 4%, being not statistically significantly different from zero. The strategy exhibits positive skewness and kurtosis and a Sharpe ratio half of selling ATM straddles. Consequently, exposure to direct credit risk is less attractive than compensation for variance risk, especially by entering into variance swaps.

4.3. Risk-adjusted returns

Next, we tackle the question of how well CVP can be attributed to established equity asset pricing risk factors. The literature on risk-factors explaining the cross-section of equities has witnessed tremendous growth in the last decade. Researchers found several hundred factors beyond the well-documented three-factor model of Fama and French (1993) or four-factor model of Carhart (1997). Lately, the vast amount of factors has been called into question. Feng, Giglio, and Xiu (2019) test 150 factors and conclude that many of them are redundant. Consequently, we resort to the recently proposed six-factor model of Fama and French (2018). Our regression model is therefore specified as follows

$$\begin{aligned} r_t =& \alpha + \beta_{MRKT}(r_t^{MRKT} - r_t^f) + \beta_{SMB}(r_t^{SMB} + \beta_{HML} r_t^{HML} + \beta_{RMW} r_t^{RMW} \\ &+ \beta_{CMA} r_t^{CMA} + \beta_{MOM} r_t^{MOM} + \epsilon_t, \end{aligned} \tag{12}$$

where r_t is the return of credit variance swaps (in month t), r^{MRKT} is the equity market return, r^f denotes the risk-free rate, r^{SMB} denotes the return of the size portfolio (SMB), r^{HML} denotes the return of the book-to-market portfolio (HML), r^{RMW} presents the return of the profitability portfolio (RMW), r^{CMA} denotes the return of the investment portfolio (CMA), and r^{MOM} is the return of the momentum portfolio (MOM). The historical portfolio returns and the risk-free rate r^f are taken from Kenneth French's website.

[Insert Table 5 near here]

Before estimating the full specification in Equation (12), we consider also a nested model by setting $\beta_{SMB} = \beta_{HML} = \beta_{RMW} = \beta_{CMA} = \beta_{MOM} = 0$. We adjust t-statistics for heteroskedasticity and autocorrelation using Newey and West (1987). Table 5 provides results. The slope coefficient of the market portfolio is positive, but not significantly different from zero. Shedding light on this, we repeat the regression with semi-variance risk premiums. As described in Table 5, payer-variance risk premiums exhibit strong, negative exposure to the market portfolio. Hence, going long payer variance swaps provides insurance against

[13] See Appendix B for details.

negative returns of the equity market portfolio. The opposite holds true for receiver variance risk premiums, probably rendering overall CVP insignificantly different from equity market performance. For direct short credit risk exposure, we conjecture a positive relationship to equity market performance since the strategy profits from improved credit conditions. Our intuition is confirmed, as shown in Table 5.

Next, we turn our attention to the estimation results of the entire model in Equation (12). As documented in Table 5, the loadings on the size, book-to-market, profitability and momentum portfolios are positive, whereas negative for the overall equity market and investment portfolio. Exposure, however, is only statistically significant for the latter two and the size portfolio. The negative slope coefficient for the size portfolio is interesting, since Carr and Wu (2009) find opposite signs for equity variance risk premiums. The difference in results may be explained by a longer sample window in Carr and Wu (2009) and the recent underperformance of the size portfolio.

We finally include ATM straddle returns in our analysis. The results in Table 5 indicate that buying ATM straddles yields returns which are not significantly related to existing risk factors or the equity market portfolio, except for the momentum portfolio. In the latter case, borderline significance and a positive exposure are documented.

4.4. Variation in variance risk premiums

Inspired by Carr and Wu (2009), Ammann and Buesser (2013), and Trolle and Schwartz (2014), we analyze time variation in CVP by running the following predictive regression

$$RV_{t,T} = \beta_0 + \beta_1 IV_{t,T} + \epsilon_t. \tag{13}$$

Carr and Wu (2009) motivate the analysis by the following equation

$$IV_{t,T} = \frac{\mathbb{E}_t^{\mathbb{P}}(M_{t,T} RV_{t,T})}{\mathbb{E}_t^{\mathbb{P}}(M_{t,T})} = \mathbb{E}_t^{\mathbb{P}}(m_{t,T} RV_{t,T}) = \mathbb{E}_t^{\mathbb{P}}(RV_{t,T}) + \mathrm{Cov}_t^{\mathbb{P}}(m_{t,T}, RV_{t,T}),$$

where $M_{t,T}$ denotes a pricing kernel, $m_{t,T} = \frac{M_{t,T}}{\mathbb{E}_t^{\mathbb{P}}(RV_{t,T})}$, and $\mathbb{P}$ denotes the real-world probability measure. Hence, under the hypothesis of zero variance risk premiums, we expect $\beta_0 = 0$ and $\beta_1 = 1$ in Equation (13). A positive slope coefficient would imply that variance swap rates are informative of future realized variance. The case of β_1 being below one would point towards time-variation in variance risk premiums. It is noteworthy that we analyze the difference in levels of realized variance and the swap rate. This represents the final payoff in dollar terms of entering a long variance swap contract.

[Insert Table 6 near here]

We estimate Equation (13) via Hansen's (1982) GMM and report results in the left panel of Table 6. t-statistics are under the null hypothesis of $\beta_0 = 0$ and $\beta_1 = 1$ and corrected for heteroscedasticity and autocorrelation according to Newey and West (1987). We consider also corridor variance contracts. Table 6 shows that slope coefficients for CVP, payer- and receiver-variance risk premiums are positive and well below one. However, only for CVP and payer variance risk premium the slope coefficients are significantly different from zero.

We redo the analysis in log-terms, i.e. we estimate the following regression

$$\ln RV_{t,T} = \beta_0 + \beta_1 \ln IV_{t,T} + \epsilon_t.$$

In this specification, risk premiums are interpreted as the logarithm of the previously introduced risk premium in Section 4.2. We report only estimates for CVP in the right panel of Table 6. Contrary to the previous finding, the slope coefficient is no longer significantly different from zero. Carr and Wu (2009) document a similar finding for equity indices and single stocks. They conclude that risk premiums defined via log returns must be more similar to a constant or independent time series than defined in dollar terms.

4.5. Comovement with equity variance and variance-of-variance risk premiums

A large body of research has concentrated on the link of CDS spreads to equity volatility and Treasury yields. From the perspective of Merton (1974), there exists a theoretical link between equity volatility, interest rates, and the leverage ratio and CDS spreads. Ericsson et al. (2009) confirms these variables as powerful determinates of CDS spreads. Consequently, we are interested in comparing the comovement of variance risk premiums on the same footing. More precisely, we study the commonality of CVP with equity variance-of-variance risk premiums and Treasury bond variance risk premiums. We also include equity variance risk premiums in our analysis. We obtain options on the S&P 500, the VIX and the exchange traded fund TLT[14] from OptionMetrics and implement the same methodology to estimate the returns on variance swaps, defined as $VSR_{t,T} = \frac{RV_{t,T}}{IV_{t,T}} - 1$. Precisely, we choose t and T each month such that T corresponds to the expiry date of CDX NA IG index options in the next calendar month and t is the trading day succeeding the expiry date of the current month. In case expiry dates for CDX NA IG swaptions do not align with S&P 500, VIX

[14] TLT tracks the performance of the Barclays Capital U.S. 20+ Year Treasury Bond Index, and hence, is exposed to long-term U.S. Treasury bonds.

or TLT options, we construct synthetic variance swap rates for S&P 500, VIX and TLT matching the time to maturity of CDX NA IG swaptions. Additionally, we create synthetic S&P 500, VIX and TLT forward prices with matching expiry dates in order to obtain realized variances. For the sake of completeness, descriptive statistics are given in Table 8.

Subsequently, we estimate the following regression

$$VRP_{t,T}^{\text{CDX NA IG}} = \alpha + \beta_{\text{S\&P 500}} VRP_{t,T}^{\text{S\&P 500}} + \beta_{\text{VIX}} VRP_{t,T}^{\text{VIX}} + \beta_{\text{TLT}} VRP_{t,T}^{\text{TLT}}, \tag{14}$$

where $VRP_{t,T}^{\text{CDX NA IG}}$ denotes CVP, and $VRP_{t,T}^{\text{S\&P 500}}$, $VRP_{t,T}^{\text{VIX}}$, and $VRP_{t,T}^{\text{TLT}}$ its analogue based on the S&P 500, VIX, and TLT, respectively. We run first univariate regressions, imposing two of the following three conditions to hold, $\beta_{\text{S\&P 500}} = 0$, $\beta_{\text{VIX}} = 0$, $\beta_{\text{TLT}} = 0$. Table 7 reports results. CVP loads significantly (at the one-percent level) and positively on S&P 500, VIX, or TLT variance swaps in isolation. Hence, payoffs to credit variance swaps are positively related to their counterparts in equity and fixed-income markets. However, the alpha remains relatively large and significant. It ranges between −30% and −39%. In terms of adjusted R^2s, equity variance-of-variance risk premiums yield the best fit by achieving 31%.

[Insert Table 7 near here]

We then consider the full specification in Equation (14). Interestingly, the exposure to equity and fixed-income variance risks is completely absorbed by variance-of-variance risks, as the former two exhibit the correct sign, but become insignificant. A large and negative alpha (-33%) still remains. Based on the outlined previous empirical findings, we expected those results for equity variance risk premiums, but not for Treasury variance risk premiums.

We repeat the analysis for payer and receiver variance risk premiums. To compare like for like, we construct semi-variance risk premiums for S& P 500, VIX and TLT. Payer variance risk premiums are associated with bad economic states of the world. The same holds true for downward equity risk premiums and upward variance-of-variance and fixed-income variance risk premiums. The same applies in reverse for receiver variance risk premiums. In estimating Equation (14), we regress credit semi-variance risk premiums on the respective counterparts for S& P 500, VIX and TLT. Results are shown in Table 7. In both cases, credit semi-variance risk premiums are not significantly related to fixed-income semi-variance risk premiums, neither in uni- nor multivariate regressions. Payer and receiver variance risk premiums significantly comove with variance-of-variance and equity variance risk premiums. However, the link appears to be stronger for variance-of-variance risk premiums. Multivariate regressions confirm this finding. However, as for total CVP, alphas remain significantly different from zero and economically large.

[Insert Table 8 near here]

4.6. Term structure of credit variance risk premiums

The results presented so far have focused on 1-month investment returns. In style of Kaeck (2018), we now concentrate on longer holding periods. Each trading day after the swaption expiry, we calculate returns of variance swaps with 2, 3, and 4 months to expiry. Table 9 documents average returns, corresponding t-statistics, and Sharpe and Stutzer ratios. Since the monthly returns are by construction not independent over time, standard errors are adjusted for heteroskedasticity and autocorrelation according to Newey and West (1987). The average risk premium is stable over the considered holding periods and remains highly statistically significant from zero. The same holds true for semi-variance risk premiums. The overall CVP yields -46% across the three different investment horizons. However, the risk-adjusted performance in terms of the Sharpe ratio is monotonically decreasing in time to maturity. The latter pattern also holds for payer- and receiver variance risk premiums. It is noteworthy that Sharpe ratios for CVP are well above 2 in absolute terms, indicating the attractiveness of CVP regardless of the investment horizon. The estimated Stutzer ratios confirm this finding.

[Insert Table 9 near here]

Table 10 provides results of applying regression model Equation (12) to returns of variance swaps with contract holding periods of 2, 3, and 4 months. The estimates confirm the overall finding in Table 9 that overall and semi-variance risk premiums cannot be explained by standard equity asset pricing factors. Strikingly, adjusted R^2s seem to increase with the holding period, cumulating in 49% for 4-month payer variance risk premium. Furthermore, the regressions reveal changes in loadings on risk-factors and their statistical significance. Exposure to investment factors is negative and highly significant for CVP at the 1-month contract, whereas it becomes positive at the 4-month contract (again highly significantly different from zero). Similarly, 4-month CVP loads negatively and statistically significant at the 5% level on book-to-market factors. Contrarily, the slope coefficient is positive, but insignificant for 1-month holding periods. Taken together, these findings indicate different investment characteristics across the holding periods. Secondly, longer-term investment seem to be better explained by standard equity risk factors. As Table 10 shows, this effect is even stronger for payer and receiver variance risk premiums.

[**Insert Table 10 near here**]

4.7. Transaction costs

To investigate whether the above documented results are robust to transaction costs, we follow Carr and Wu (2009) by assuming that investors short realized variance each month by entering a short variance swap the trading day after swaption expiry and holding the position until maturity in the next month. Consequently, we reconstruct synthetic variance swap rates using bid instead of mid option prices. The incorporation of transaction costs in our analysis is an important task. Driessen et al. (2009) show that correlation risk premiums yield Sharpe ratios above equity markets only before transaction costs.

Markit provides us with bid and ask option prices for the latest on-the-run series. To obtain bid prices for previous series, we proceed as follows. We treat the bid-ask spread relative to the mid price as a function of time to maturity and moneyness level. Subsequently, we use k-nearest-neighbours to find the bid option price for swaptions with missing bid-ask spread. Our procedure implicitly assumes that liquidity patterns in the swaptions remain constant over our entire sample period. Trolle and Schwartz (2014) rest on the same assumption while contacting major investment banks to obtain indicative bid-ask spreads at the sample end. Subsequently, the authors form three different strike buckets and apply to each a representative bid-ask spread. Since Trolle and Schwartz (2014) concentrate on a single maturity, we would have to introduce a second dimension to such an approach. We believe that, instead of constructing such a two-dimensional grid, it is more intuitive to use k-nearest-neighbours.

[**Insert Figure 4 near here**]

The left graph in Figure 4 depicts the implied variances $IV_{t,T}$ estimated by bid swaption prices for each month in our sample, including also the realized variances (the latter are not affected by using bid swaption prices instead of mid prices). The right graph shows the corresponding returns as defined in Section 4.2. The returns appear to be still highly leptokurtic. However, we observe more occurrences with positive returns. Moreover, positive returns tend to be larger on average, when compared to our previous findings based on mid-quotes.

[**Insert Table 11 near here**]

Table 11 reports the average returns for investment horizons spanning 1 to 4 months. CVP remains highly negative and statistically significant across all investment horizons.

However, the average 1-month return is reduced by 21 percentage points to −20%, confirming the visual inspection. Average returns for longer periods range between −33% and −36%. Similarly, 1-month payer variance risk premiums are reduced by 14 percentage points to −36%, and remain statistically highly significant. The reduction in risk premiums ceases with increasing investment horizon, e.g., payer variance risk premium at the 4-month horizon amounts to −60% when estimated from bid-quotes, whereas it amounts to −64% when calculated from mid-prices. Interestingly, receiver variance risk premiums become positive at the 1-month horizon and negative for longer periods. However, mean returns are not significantly different from zero, indicating that variance risk in states of the world where credit quality improves is not priced.

4.8. Predictive power of credit implied volatility

In the realm of equity markets, the VIX is known as a fear gauge, due to its tendency to rise in times of negative equity market returns. Moreover, the VIX proves to exhibit predictive power for future economic activity and financial stability (see Bekaert and Hoerova, 2014). In the following, inspired by Choi et al. (2017), we analyze whether credit implied variance and the slope of the credit implied variance term structure contain predictive power for financial stress, measured by the St. Louis Fed Stress Index (STLFSI, hereafter).[15]

We use implied credit volatility over the next 45 days and denote it CIV for brevity. Furthermore, we measure the slope of the term structure of implied variances, $\text{slope}^{\text{CIV}}$, by the difference between 105-day and 45-day implied variances. To test the predictive power of CIV and $\text{slope}^{\text{CIV}}$, we examine the following regression model on a weekly basis for different horizons, n, ranging from 0 to 8 weeks:

$$\text{STLFSI}_{t+n} = \beta_n^{\text{CIV}} \text{CIV}^2 + \beta_n^{\text{slope CIV}} \text{slope}^{\text{CIV}} + \epsilon_{t+n}, \quad n \in \{0, 4, 8\}.$$

We report results in Table 12 and concentrate first on univariate regressions, setting either β_n^{CIV} or $\beta_n^{\text{slope CIV}}$ to zero. We conjecture a positive (negative) relationship between STLFSI and credit implied variances (its term structure). In times of stress, credit implied variance rises and the term structure of credit implied variances inverts. Our results confirm this hypothesis. CIV^2 is positively and significantly related to STLFSI, regardless of the horizon considered. Any one standard deviation change in CIV^2 yields a 0.4 to 0.6 standard deviation increase in STLFSI. A negative and significant effect is estimated for the slope

[15] The STLFSI uses 18 weekly data series (including interest rates, yield spreads, and other indicators such as the VIX and the MOVE) and principal component analysis to measure stress in the financial markets. A reading above 0 indicates above-average financial market stress, whereas values below zero indicate below-average financial market stress.

of the credit implied variance term structure. Albeit, the effect is weaker than for credit implied variance and rendered insignificant in the multivariate setting. However, CIV^2 still poses strong predictive power for financial stress. At contemporaneous and short horizons, the adjusted R^2s is above 33%. The power diminishes with the horizon considered, as the adjusted R^2 drops sharply by half for the longest horizon.

[Insert Table 12 near here]

STLFSI includes VIX and MOVE in its construction. Therefore, one might argue that a high correlation between credit implied volatility and equity and fixed income volatility drive our results. As a robustness check, we redo the analysis, but with a modified version of STLFSI. In a first stage, we orthogonalize STLFSI with respect to VIX and MOVE. We then regress the orthogonalized STLFSI onto CIV^2 and its term structure. Table 13 shows that we still find predictive power of CIV^2.

5. Conclusion

Using a novel data set of swaptions written on the CDX North America Investment Grade index, this paper studies credit variance risk premiums via the notion of variance swaps. We document a highly significant monthly premium of -42%, well above equity or Treasury bond variance risk premiums. Moreover, credit variance risk premiums exhibit excellent risk-adjusted performance as the annualized Sharpe ratio is approximately 6. We dissect credit variance risk premiums into payer and receiver variance risk premiums by means of corridor variance swaps. The former are associated with economically unfavourable states of the world, in contrast to the latter. We find that both semi-variance risk premiums are strongly negative and significant. However, payer variance risk premiums amount to roughly twice receiver variance risk premiums. Additionally, we study whether well-known equity asset pricing risk factors are able to explain credit variance risk premiums. The Fama French six-factor model can only explain a very small portion of variance risk premiums. Our results remain robust if we vary the investment horizon of credit variance swaps, and account for transaction costs. Finally, we analyze the information content of credit implied volatility. We find that the level of credit implied volatility is a highly useful predictor of financial stress.

Appendix A. Synthesizing Variance Swap Contracts

First, we assume that $\kappa^{\mathrm{a}}_{\mathrm{t,T}}$ follows a continuous process. This allow us to write

$$\frac{\mathrm{d}\,\kappa^{\mathrm{a}}_{\mathrm{t,T}}}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} = \sigma_t dW_t^{\mathbb{A}},$$

where $dW_t^{\mathbb{A}}$ is a standard Brownian motion under the risky annuity measure $\mathbb{A}$, and σ_t denotes the instantaneous volatility.

We follow Bakshi and Madan (2000), Carr and Madan (2001), and Bakshi, Kapadia, and Madan (2003) and Bondarenko (2014). For any twice-differentiable function g and any fixed positive x, we have

$$\begin{aligned} g(\kappa^a_{T,T}) =& g(x) + g'(x)\left(\kappa^a_{T,T} - x\right) + \int_0^x g''(\kappa)\left(K - \kappa^a_{T,T}\right)^+ d\kappa \\ &+ \int_x^\infty g''(\kappa)\left(\kappa^a_{T,T} - \kappa\right)^+ d\kappa. \end{aligned}$$

Specifically for $x = \kappa^a_{t,T}$, we obtain

$$\begin{aligned} g(\kappa^a_{T,T}) =& g(\kappa^a_{t,T}) + g'(\kappa^a_{t,T})\left(\kappa^a_{T,T} - \kappa^a_{t,T}\right) + \int_0^{\kappa^a_{t,T}} g''(\kappa)\left(K - \kappa^a_{T,T}\right)^+ d\kappa \\ &+ \int_{\kappa^a_{t,T}}^\infty g''(\kappa)\left(\kappa^a_{T,T} - \kappa\right)^+ d\kappa. \end{aligned}$$

Taking as $g(\kappa) = \log\kappa$ yields

$$\log\kappa^a_{T,T} = \log\kappa^a_{t,T} + \frac{1}{\kappa^a_{t,T}}\left(\kappa^a_{T,T} - \kappa^a_{t,T}\right) - \int_0^{\kappa^a_{t,T}} \frac{1}{\kappa^2}\left(K - \kappa^a_{T,T}\right)^+ d\kappa - \int_{\kappa^a_{t,T}}^\infty \frac{1}{\kappa^2}\left(\kappa^a_{T,T} - \kappa\right)^+ d\kappa. \tag{A.1}$$

Ito's lemma implies that

$$\mathrm{d}(\log\kappa^{\mathrm{a}}_{\mathrm{t,T}}) = \frac{\mathrm{d}\,\kappa^{\mathrm{a}}_{\mathrm{t,T}}}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} - \frac{1}{2}\sigma_t^2 dt.$$

Therefore, the quadratic variation of $\kappa^{\mathrm{a}}_{\mathrm{t,T}}$ can be expressed as

$$
\begin{aligned}
\int_t^T \sigma_s^2 ds =& - 2\log\frac{\kappa^2_{T,T}}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} + \int_t^T \frac{\mathrm{d}\kappa^a_{s,T}}{\kappa^a_{s,T}} \\
=&2\left(\frac{\kappa^2_{T,T}-\kappa^{\mathrm{a}}_{\mathrm{t,T}}}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} - \log\frac{\kappa^2_{T,T}}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}\right) + 2\int_t^T\left(\frac{1}{\kappa^a_{s,T}} - \frac{1}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}\right)\mathrm{d}\kappa^a_{s,T} \\
=&2\left(\int_0^{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} \frac{\left(\kappa-\kappa^a_{T,T}\right)^+}{\kappa^2}\mathrm{d}\kappa + \int_{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}^{\infty} \frac{\left(\kappa^a_{T,T}-\kappa\right)^+}{\kappa^2}\mathrm{d}\kappa\right) \\
&+ 2\int_t^T\left(\frac{1}{\kappa^a_{s,T}} - \frac{1}{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}\right)\mathrm{d}\kappa^a_{s,T}.
\end{aligned} \tag{A.2}
$$

Next, we take expectations under the risky annuity measure $\mathbb{A}$ of eq. (A.2), multiply by A^a_t and use that $\kappa^a_{t,T}$ is a martingale under $\mathbb{A}$. This yields

$$
\begin{aligned}
A^a_t\mathbb{E}^{\mathbb{A}}_t\left[\int_t^T \sigma_s^2 ds\right] =& - 2A^a_t\mathbb{E}^{\mathbb{A}}_t\left[\log\kappa^a_{T,T} - \log\kappa^{\mathrm{a}}_{\mathrm{t,T}}\right] \\
=&2A^a_t\mathbb{E}^{\mathbb{A}}\left[\int_0^{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} \frac{\left(\kappa-\kappa^a_{T,T}\right)^+}{\kappa^2}\mathrm{d}\kappa + \int_{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}^{\infty} \frac{\left(\kappa^a_{T,T}-\kappa\right)^+}{\kappa^2}\mathrm{d}\kappa\right] \\
=&2\left(\int_0^{\kappa^{\mathrm{a}}_{\mathrm{t,T}}} \frac{\mathcal{R}_T(t,\kappa)}{\kappa^2}\mathrm{d}\kappa + \int_{\kappa^{\mathrm{a}}_{\mathrm{t,T}}}^{\infty} \frac{\mathcal{P}_T(t,\kappa)}{\kappa^2}\mathrm{d}\kappa\right).
\end{aligned}
$$

Finally, we relay the assumption on continuity of $\kappa^{\mathrm{a}}_{\mathrm{t,T}}$ and follow Bondarenko (2014). eq. (7) can be rewritten as

$$
\begin{aligned}
RV_{t,T} =& - 2\log\frac{\kappa^a_{t_n,T}}{\kappa^a_{t_0,T}} + 2\sum_{i=1}^n\left(\frac{\kappa^a_{t_i,T}-\kappa^a_{t_{i-1},T}}{\kappa^a_{t_{i-1},T}}\right) \\
=&2\left(\frac{\kappa^a_{t_n,T}-\kappa^a_{t_0,T}}{\kappa^a_{t_0,T}} - \log\frac{\kappa^a_{t_n,T}}{\kappa^a_{t_0,T}}\right) + 2\sum_{i=1}^n\left(\frac{1}{\kappa^a_{t_{i-1},T}} - \frac{1}{\kappa^a_{t_0,T}}\right)\left(\kappa^a_{t_i,T}-\kappa^a_{t_{i-1},T}\right) \\
=&2\left(\int_0^{\kappa^a_{t,T}} \frac{1}{\kappa^2}\left(K-\kappa^a_{T,T}\right)^+ d\kappa + \int_{\kappa^a_{t,T}}^{\infty} \frac{1}{\kappa^2}\left(\kappa^a_{T,T}-\kappa\right)^+ d\kappa\right) \\
&+ 2\sum_{i=1}^n\left(\frac{1}{\kappa^a_{t_{i-1},T}} - \frac{1}{\kappa^a_{t_0,T}}\right)\left(\kappa^a_{t_i,T}-\kappa^a_{t_{i-1},T}\right),
\end{aligned}
$$

where the last equation follows from eq. (A.1).

Appendix B. Credit risk premiums

To get a better understanding of (semi-) variance risk premiums, we study risk premiums with direct exposure to credit risk. Therefore, we consider the following strategy. Each month, we enter into a forward-starting CDIS (receiving the fixed leg, paying the floating leg in the underlying CDIS strategy) one day after the expiry date of CDX NA IG index options, denoted by t_0. The expiration date of the forward-starting CDIS, denoted by T, coincides with the expiry date of CDX NA IG index options in the succeeding month. We hold the forward-starting CDIS until maturity, at which it becomes the spot CDIS. Denote by $\kappa_{t,T}$ the forward CDIS spread at time $t \in [t_0, T]$. Since CDIS are traded with a standard coupon κ for a given notional N, the value of the forward-starting CDIS at $t \in [t_0, T]$ is

$$S^n_{t,T} = A^n_{t,T} \left(\kappa^n_{t,T} - \kappa \right) \times N.$$

This implies that the profit and loss at T is

$$\left(S^n_{T,T} - S^n_{t,T} \right) \times N = \left[\left(A^n_{T,T} \left(\kappa^n_{T,T} - \kappa \right) \right) - \left(A^n_{t,T} \left(\kappa^n_{t,T} - \kappa \right) \right) \right] \times N.$$

The payoffs to this strategy are fundamentally different from the return definition of credit variance swaps. Precisely, the payoff bearing direct credit risk is the profit or loss for a given, time-invariant notional investment N in forward-CDIS. In order to make the latter comparable to credit variance risk premiums, we borrow the idea of Duarte, Longstaff, and Yu (2007). We assume an initial amount of capital, X, which is needed to enter into a forward-CDIS. X is not necessarily the same as N. Accordingly, the excess return of our strategy reads

$$\frac{\left(S^n_{T,T} - S^n_{t,T} \right) \times N}{X}.$$

We adjust X in order to generate the same unconditional volatility of our estimated credit variance risk premium. Trolle and Schwartz (2014) employ a similar approach for measuring variance and skewness risk premiums in USD and EUR denominated swaptions markets.

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Table 1: **CDX North America Investment Grade 5 year options data set**

This table summarizes information on options written on the CDX North America Investment Grade 5 year index. The options data is grouped into buckets depending on the time to maturity. For each bucket, we report the number of days with observed quotes, average and median time to maturity, moneyness level, and number of strikes per maturity. Panel A displays the statistics on our sample across on-the-run and off-the-run, whereas Panel B and Panel C focus soley on on-the-run and off-the-run, respectively.

		Maturity Bucket						
		Days $\leq$ 30	30 $<$ Days $\leq$ 60	60 $<$ Days $\leq$ 90	90 $<$ Days $\leq$ 120	120 $<$ Days $\leq$ 150	150 $<$ Days $\leq$ 180	Days $>$ 180
Panel A: On- and off-the-run								
# Active Days		1381	1399	1451	1364	1051	704	538
Time To Maturity	Mean	17.76	45.67	75.04	105.49	135.33	164.15	205.88
	Median	19	47	76	105	134	163	198
Moneyness	Mean	0.89 - 1.28	0.83 - 1.52	0.80 - 1.62	0.78 - 1.67	0.77 - 1.71	0.76 - 1.69	0.75 - 1.65
	Median	0.89 - 1.25	0.83 - 1.50	0.80 - 1.62	0.78 - 1.66	0.77 - 1.69	0.76 - 1.69	0.75 - 1.65
Number of Strikes	Mean	9.20	13.66	15.36	15.46	15.44	14.87	12.90
	Median	9	14	15	15	15	15	12
Panel B: On-the-run								
# Active Days		1381	1399	1451	1364	1051	704	538
Time To Maturity	Mean	17.72	45.61	75.01	105.47	135.33	164.13	205.96
	Median	19	47	76	105	134	163	198
Moneyness	Mean	0.89 - 1.28	0.83 - 1.52	0.80 - 1.62	0.78 - 1.67	0.77 - 1.71	0.76 - 1.69	0.75 - 1.65
	Median	0.89 - 1.25	0.83 - 1.50	0.80 - 1.62	0.78 - 1.66	0.77 - 1.69	0.76 - 1.69	0.75 - 1.65
Number of Strikes	Mean	9.19	13.67	15.37	15.51	15.46	14.89	12.91
	Median	9	14	15	15	15	15	12
Panel C: Off-the-run								
# Active Days		16	17	14	15	2	9	2
Time To Maturity	Mean	21.75	50.53	77.73	106.82	134.50	165.78	183.50
	Median	26	55	83	106	134.50	162	183.50
Moneyness	Mean	0.88 - 1.32	0.83 - 1.52	0.81 - 1.58	0.82 - 1.53	0.84 - 1.55	0.77 - 1.58	0.83 - 1.71
	Median	0.88 - 1.31	0.83 - 1.47	0.81 - 1.62	0.82 - 1.52	0.84 - 1.55	0.79 - 1.56	0.83 - 1.71
Number of Strikes	Mean	9.69	13.24	14.33	11.82	9	13	10.50
	Median	9.50	14	15	12	9	13	10.50

Table 2: **Summary statistics on credit implied volatility**
This table reports the summary statistics of credit implied volatilities for three maturities (45, 75, and 105 days) over the sample period from March 2012 to September 2018. Columns (3)-(8) report the mean, standard deviation, skewness, kurtosis, minimum, and maximum. Levels and first differences of log values of the three implied volatility time series are considered.

Type	Maturity	Mean	Std	Skewness	Kurtosis	Min	Max
Levels	45	0.474	0.066	0.603	3.101	0.336	0.719
	75	0.487	0.057	0.395	2.832	0.361	0.673
	105	0.495	0.052	0.282	2.763	0.376	0.647
Log changes	45	-0.000	0.039	0.324	4.534	-0.131	0.185
	75	-0.000	0.032	0.293	4.439	-0.104	0.158
	105	-0.000	0.029	0.221	4.496	-0.103	0.146

Table 3: **Principal component analysis of credit implied volatility**
This table reports the summary statistics of performing principal component analysis on log-changes of credit implied volatilities for three maturities (45, 75, and 105 days) over the sample period from March 2012 to September 2018. Columns (1)-(3) display the coefficients on the three maturities. The second to last row denotes the amount of variation explained by the first (first cell), second (second cell), and third (third cell) principal component.

Maturity	PC 1	PC 2	PC 3
45	0.665	0.562	0.492
75	0.656	-0.125	-0.744
105	0.357	-0.818	0.452
Variance (%)	96.394	3.274	0.332
Cumulative variance (%)	96.394	99.668	100.000

Table 4: **Summary statistics on credit variance risk premiums**

This table reports monthly summary statistics for the CVP and payer and receiver credit variance risk premiums over the sample period from March 2012 to September 2018. CVP is given as the monthly return defined by $RV_{t,T}/IV_{t,T} - 1$, where $IV_{t,T}$ is the implied variance and $RV_{t,T}$ the realized daily variance over a monthly period. The payer and receiver variance risk premium is defined analogously. Columns (2)-(9) report the mean, standard deviation, maximum, skewness, kurtosis, Sortino ratio, Stutzer ratio and Sharpe ratio. Standard errors are computed using Newey and West (1987) accounting for autocorrelation and hetereoscedasticity with optimal bandwidth. Sharpe ratios are corrected for return-autocorrelation using the approach of Lo (2002). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Strategy	Mean	Std	Max	Skewness	Kurtosis	Sortino Ratio	Stutzer Ratio	Sharpe Ratio
CVP	-0.42***	0.28	0.74	1.22	5.37	-2.01	-1.21	-5.62
	(-14.06)							
CVP Payer	-0.51***	0.52	1.29	1.22	4.02	-1.86	-0.86	-4.05
	(-8.75)							
CVP Receiver	-0.26***	0.53	1.52	0.95	4.02	-0.87	-0.46	-1.99
	(-4.32)							
ATM straddle	-0.21***	0.56	1.30	0.65	2.72	-0.75	-0.37	-1.25
	(-3.06)							
CDS	0.04	0.28	1.06	0.19	4.94	0.21	0.15	0.59
	(1.49)							

Table 5: **Risk-adjusted variance risk premiums**

This table reports the estimation results from regression the returns of trading strategies on the equity market excess return (MRKT), size (SMB), book-to-market (HML), (RMW), (CMA) and momentum (MOM) factors. Column (8) reports the adjusted R^2 of the regression. t-statistics are given in parentheses and adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

Strategy	Alpha	MRKT	SMB	HML	RMW	CMA	MOM	Adj. R^2
CVP	-0.40***	-1.62						0.02
	(-11.40)	(-1.10)						
	-0.40***	-2.44**	3.08***	2.49	0.41	-6.48*	0.09	0.08
	(-11.94)	(-2.29)	(2.64)	(1.47)	(0.17)	(-1.92)	(0.08)	
CVP Payer	-0.42***	-8.31***						0.22
	(-6.24)	(-4.20)						
	-0.42***	-9.46***	4.94**	5.46*	1.74	-9.36*	0.95	0.24
	(-6.99)	(-5.23)	(2.07)	(1.72)	(0.45)	(-1.77)	(0.58)	
CVP Receiver	-0.36***	8.62***						0.23
	(-7.80)	(4.01)						
	-0.34***	8.17***	0.90	-2.11	-1.24	-0.65	-1.57	0.19
	(-6.70)	(2.99)	(0.26)	(-0.66)	(-0.35)	(-0.19)	(-1.16)	
ATM straddle	-0.24***	2.18						0.00
	(-3.69)	(1.01)						
	-0.25***	1.94	5.63	5.83	3.92	-0.27	3.99*	0.01
	(-3.84)	(0.82)	(1.51)	(1.39)	(0.87)	(-0.05)	(1.80)	
CDS	-0.04*	6.78***						0.53
	(-1.69)	(6.54)						
	-0.01	5.81***	-0.83	0.81	-2.86**	-1.18	-2.16***	0.56
	(-0.83)	(5.83)	(-0.64)	(0.69)	(-2.02)	(-0.58)	(-3.08)	

Table 6: **Expectation hypothesis regressions**

This table shows results for predictive regressions. t-statistics are under the null hypothesis of $\beta_0 = 0$ and $\beta_1 = 1$ and are adjusted for heteroscedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

	$RV_{t,T} = \beta_0 + \beta_1 IV_{t,T} + \epsilon_t$			$\ln RV_{t,T} = \beta_0 + \beta_1 \ln IV_{t,T} + \epsilon_t$		
Strategy	β_0	β_1	R^2	β_0	β_1	R^2
CVP	0.00	0.42***	0.20	-1.06	0.90	0.30
	(0.98)	(-3.53)		(-1.17)	(-0.43)	
CVP Payer	0.00**	0.19***	0.02			
	(2.40)	(-9.13)				
CVP Receiver	0.00	0.69	0.16			
	(0.10)	(-0.81)				

Table 7: **Comovement with equity market variance risk premiums**
The table presents the results from regression credit variance risk premiums (CVP) on S&P 500 and VIX variance risk premiums. Column (5) reports the adjusted R^2 of the regression. t-statistics are given in parentheses and adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until December 2017.

Strategy	Alpha	S&P 500	VIX	TLT	Adj. R^2
CVP	-0.30***	0.29***			0.22
	(-5.93)	(3.35)			
	-0.37***		0.21***		0.31
	(-11.70)		(3.59)		
	-0.39***			0.20***	0.06
	(-9.83)			(2.83)	
	-0.33***	0.13	0.15**	0.04	0.32
	(-9.07)	(1.35)	(2.07)	(0.55)	
CVP Payer	-0.31***	0.45***			0.36
	(-3.80)	(3.88)			
	-0.43***		0.29***		0.29
	(-6.51)		(4.38)		
	-0.53***			0.14	0.03
	(-8.50)			(1.21)	
	-0.33***	0.33**	0.12	0.03	0.38
	(-4.27)	(2.47)	(1.56)	(0.42)	
CVP Receiver	-0.10	0.51***			0.22
	(-1.43)	(4.74)			
	-0.23***		0.26***		0.12
	(-3.97)		(4.81)		
	-0.29***			-0.08	-0.00
	(-4.03)			(-1.19)	
	-0.14**	0.43***	0.12	-0.07	0.23
	(-2.16)	(4.01)	(1.42)	(-0.96)	

Table 8: **Equity variance, variance-of-variance and bond-variance risk premiums**
This table reports monthly summary statistics for the equity variance (calculated from S%P 500 index options), equity variance-of-variance (calculated from VIX index options) and bond variance (calculated from options on the ETF TLT) risk premiumsover the sample period from March 2012 to September 2018. Teh variance risk premium is given as the monthly return defined by $VRP^i_{t,T} = RV_{t,T}/IV_{t,T} - 1$, where $IV_{t,T}$ is the implied variance and $RV_{t,T}$ the realized daily variance over a monthly period and $i \in \{\text{CDX NA IG, S\&P 500, VIX, TLT}\}$. Columns (2)-(9) report the mean, standard deviation, maximum, skewness, kurtosis, Sortino ratio, Stutzer ratio and Sharpe ratio. Standard errors are computed using Newey and West (1987) accounting for autocorrelation and hetereoscedasticity with optimal bandwidth. Sharpe ratios are corrected for return-autocorrelation using the approach of Lo (2002). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until December 2017.

Strategy	Mean	Std	Max	Skewness	Kurtosis	Sortino Ratio	Stutzer Ratio	Sharpe Ratio
SPX	-0.43***	0.40	1.68	2.93	14.48	-1.94	-0.79	-2.88
	(-8.70)							
VIX	-0.25***	0.68	2.16	1.77	5.90	-1.12	-0.34	-1.83
	(-3.34)							
TLT	-0.17***	0.34	1.13	1.24	5.33	-0.92	-0.45	-1.57
	(-4.06)							

Table 9: **Credit variance risk premium (monthly term structure)**

This table documents the average credit variance risk premium defined as $RV_{t,T}/IV_{t,T} - 1$, where $IV_{t,T}$ denotes the implied variance and $RV_{t,T}$ the realized daily variance. Risk premiums are reported for holding periods of 2, 3 and 4 months. On each month, the first trade date after swaption expiry is selected and credit variance contract returns are computed from swaptions with 2, 3 and 4 months to expiry. Results for payer and receiver variance contracts are also reported. t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). All Sharpe ratios account for return-autocorrelation according to Lo (2002). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

	2 months			3 months			4 months		
Strategy	Mean	Sharpe Ratio	Stutzer Ratio	Mean	Sharpe Ratio	Stutzer Ratio	Mean	Sharpe Ratio	Stutzer Ratio
CVP	-0.46***	-3.94	-1.92	-0.47***	-3.18	-2.14	-0.47***	-2.89	-2.23
	(-15.11)			(-14.56)			(-13.81)		
CVP Payer	-0.59***	-2.99	-1.22	-0.63***	-2.55	-1.38	-0.66***	-2.24	-1.46
	(-10.73)			(-11.42)			(-10.74)		
CVP Receiver	-0.27***	-1.17	-0.51	-0.24***	-0.85	-0.49	-0.23***	-0.79	-0.55
	(-4.46)			(-3.80)			(-3.79)		

Table 10: **Risk-adjusted variance risk premiums (term structure)**
This table reports the estimation results from regression the returns of credit variance risk premiums on the equity market excess return (MRKT), size (SMB), book-to-market (HML), (RMW), (CMA) and momentum (MOM) factors. Variance contracts are held over periods for 2 (Panel A), 3 (Panel B) and 4 (Panel C) months. Column (8) reports the adjusted R^2 of the regression. t-statistics are given in parentheses and adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

Strategy	Alpha	MRKT	SMB	HML	RMW	CMA	MOM	Adj. R^2
Panel A: 2-month contract								
CVP	-0.45***	-0.60						-0.00
	(-13.53)	(-0.74)						
	-0.43***	-1.33*	1.48	0.45	-1.35	-1.13	-0.18	0.02
	(-12.16)	(-1.80)	(1.41)	(0.40)	(-1.20)	(-0.65)	(-0.23)	
CVP Payer	-0.44***	-6.22***						0.32
	(-7.97)	(-7.04)						
	-0.44***	-7.12***	4.07**	1.39	-0.22	-1.94	1.04	0.36
	(-8.20)	(-8.84)	(2.39)	(0.96)	(-0.14)	(-0.84)	(0.95)	
CVP Receiver	-0.45***	7.76***						0.37
	(-10.54)	(5.97)						
	-0.42***	7.37***	-2.31	-0.89	-2.35	0.31	-1.94**	0.36
	(-11.86)	(4.96)	(-1.08)	(-0.37)	(-0.97)	(0.11)	(-2.54)	
Panel B: 3-month contract								
CVP	-0.44***	-0.82						0.02
	(-12.27)	(-1.31)						
	-0.42***	-1.27**	1.67*	-0.60	-0.84	1.59	-0.25	0.08
	(-11.98)	(-2.48)	(1.67)	(-0.76)	(-0.97)	(1.25)	(-0.47)	
CVP Payer	-0.45***	-5.25***						0.34
	(-8.06)	(-8.98)						
	-0.47***	-5.16***	4.74***	-0.55	3.20**	3.40*	1.77***	0.43
	(-9.92)	(-7.27)	(2.77)	(-0.56)	(2.27)	(1.86)	(2.74)	
CVP Receiver	-0.43***	5.39***						0.25
	(-7.99)	(4.89)						
	-0.36***	4.29***	-2.60**	-0.59	-5.72***	-1.28	-3.02***	0.33
	(-7.14)	(4.16)	(-2.10)	(-0.56)	(-3.84)	(-0.66)	(-4.17)	
Panel C: 4-month contract								
CVP	-0.42***	-1.17**						0.07
	(-9.42)	(-2.32)						
	-0.38***	-1.58***	1.48**	-1.25**	-0.11	2.70**	-0.14	0.17
	(-12.32)	(-3.89)	(2.19)	(-2.37)	(-0.14)	(2.51)	(-0.32)	
CVP Payer	-0.41***	-5.20***						0.40
	(-6.21)	(-8.28)						
	-0.40***	-5.37***	4.02***	-1.22	3.89***	4.82**	1.65***	0.49
	(-6.92)	(-8.78)	(3.58)	(-1.41)	(3.04)	(2.50)	(2.94)	
CVP Receiver	-0.44***	4.28***						0.25
	(-6.91)	(4.52)						
	-0.37***	3.75***	-2.05***	-1.17**	-4.57***	-0.62	-2.49***	0.31
	(-13.29)	(7.58)	(-3.19)	(-2.23)	(-5.52)	(-0.66)	(-4.83)	

Table 11: **Credit variance risk premiums from bid option quotes**

This table documents the average credit variance risk premium defined as $RV_{t,T}/IV_{t,T} - 1$, where $IV_{t,T}$ denotes the implied variance computed from bid option quotes and $RV_{t,T}$ the realized daily variance. Risk premiums are reported for holding periods of 1, 2, 3 and 4 months. On each month, the first trade date after swaption expiry is selected and credit variance contract returns are computed from swaptions with 1, 2, 3 and 4 months to expiry. Results for payer and receiver variance contracts are also reported. t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). All Sharpe ratios account for return-autocorrelation according to Lo (2002). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

	1 month		2 months		3 months		4 months	
Strategy	Mean	Sharpe Ratio	Mean	Sharpe Ratio	Mean	Sharpe Ratio	Mean	Sharpe Ratio
CVP	-0.20***	-1.86	-0.35***	-2.37	-0.39***	-2.26	-0.40***	-2.14
	(-4.69)		(-9.19)		(-10.36)		(-10.24)	
CVP Payer	-0.37***	-2.21	-0.52***	-2.28	-0.59***	-2.14	-0.62***	-1.91
	(-4.73)		(-8.18)		(-9.57)		(-9.17)	
CVP Receiver	0.09	0.51	-0.03	-0.11	-0.05	-0.16	-0.07	-0.22
	(1.08)		(-0.41)		(-0.70)		(-1.03)	

Table 12: **Predictive regressions St. Louis Fed Stress Index**
This table reports the estimation results from weekly regressions of the St. Louis Fed Stress Index (STLFSI) onto CIV squared and the slope of CIV, $\text{slope}^{\text{CIV}}$, i.e.

$$\text{STLFSI}_{t+n} = \beta_n^{\text{CIV}}\text{CIV}^2 + \beta_n^{\text{slope CIV}}\text{slope}^{\text{CIV}} + \epsilon_{t+n}, n \in \{0, 4, 8, 12\}.$$

CIV denotes credit implied volatility with 45 days to maturity. $\text{slope}^{\text{CIV}}$ is measured by the difference between implied variance with 105 and 45 days to maturity. All variables are standardized, that means de-meaned and divided by their respective standard deviation. t-statistics are given in parentheses and adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.The sample period runs from April 2012 until August 2018.

CIV^2	$\text{slope}^{\text{CIV}}$	Adj. R^2
Panel A: Contemp.		
0.63***		0.40
(6.10)		
	-0.33***	0.11
	(-2.78)	
0.72***	0.14	0.41
(7.85)	(1.13)	
Panel B: 4 weeks		
0.57***		0.33
(5.90)		
	-0.22**	0.05
	(-2.13)	
0.72***	0.24**	0.36
(8.12)	(2.20)	
Panel C: 8 weeks		
0.40***		0.17
(4.50)		
	-0.20***	0.04
	(-3.08)	
0.45***	0.08	0.17
(3.56)	(0.83)	

Table 13: **Predictive regressions St. Louis Fed Stress Index (orthogonalized)**
This table reports the estimation results from weekly regressions of the St. Louis Fed Stress Index ($\hat{\text{STLFSI}}$), orthogonalized with respect to VIX and MOVE, onto CIV squared and the slope of CIV, $\text{slope}^{\text{CIV}}$, i.e.

$$\hat{\text{STLFSI}}_{t+n} = \beta_n^{\text{CIV}} \text{CIV}^2 + \beta_n^{\text{slope CIV}} \text{slope}^{\text{CIV}} + \epsilon_{t+n}, n \in \{0, 4, 8, 12\}.$$

CIV denotes credit implied volatility with 45 days to maturity. $\text{slope}^{\text{CIV}}$ is measured by the difference between implied variance with 105 and 45 days to maturity. All variables are standardized, that means de-meaned and divided by their respective standard deviation. t-statistics are given in parentheses and adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. The sample period runs from April 2012 until August 2018.

CIV^2	$\text{slope}^{\text{CIV}}$	Adj. R^2
Panel A: Contemp.		
0.02		0.00
(0.20)		
	0.19	0.04
	(1.60)	
0.24**	0.34**	0.07
(2.15)	(2.57)	
Panel B: 4 weeks		
0.32***		0.10
(3.26)		
	-0.19**	0.04
	(-1.98)	
0.34***	0.03	0.10
(2.77)	(0.25)	
Panel C: 8 weeks		
0.29***		0.08
(3.01)		
	-0.25***	0.06
	(-3.41)	
0.22*	-0.11	0.09
(1.84)	(-1.20)	

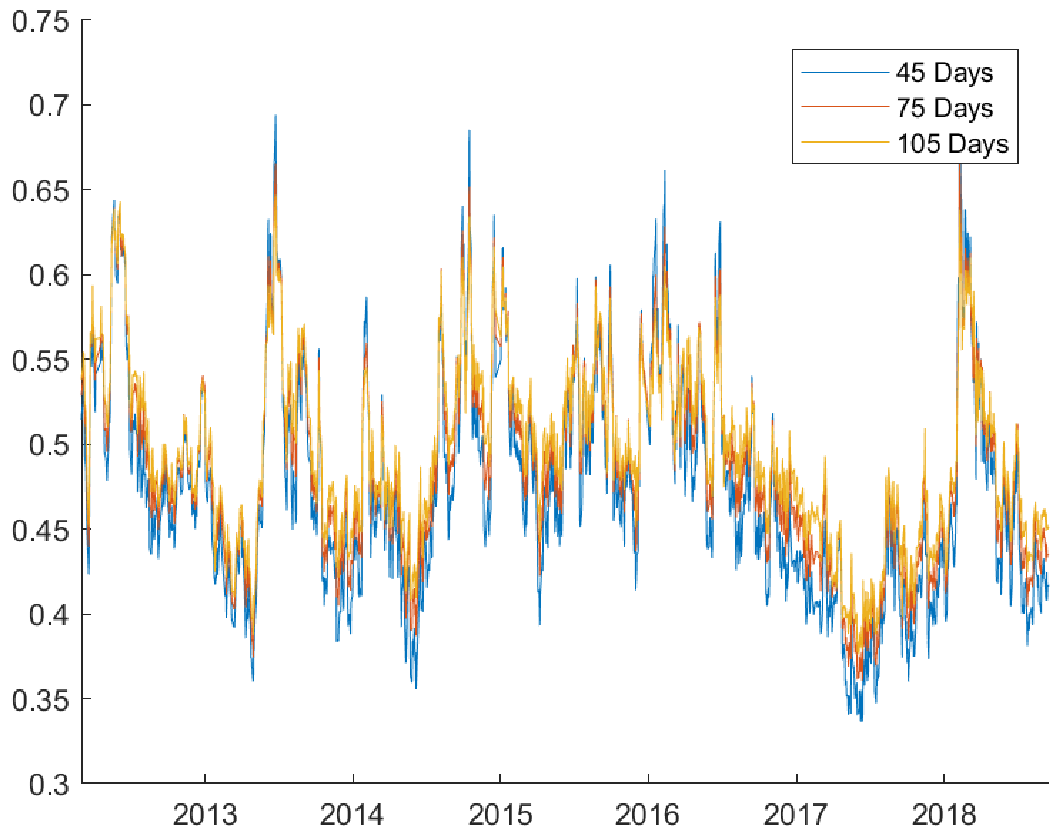

Fig. 1. Credit implied volatility.
The figure shows the time series of credit implied volatility for three different constant maturities (45, 75, and 105 days) over the sample period from March 2012 to September 2018. Implied volatility is the annualized square-root of implied variance; that is $\sqrt{(T-t)IV_{t,T}}$, where $IV_{t,T}$ is defined in eq. (8).

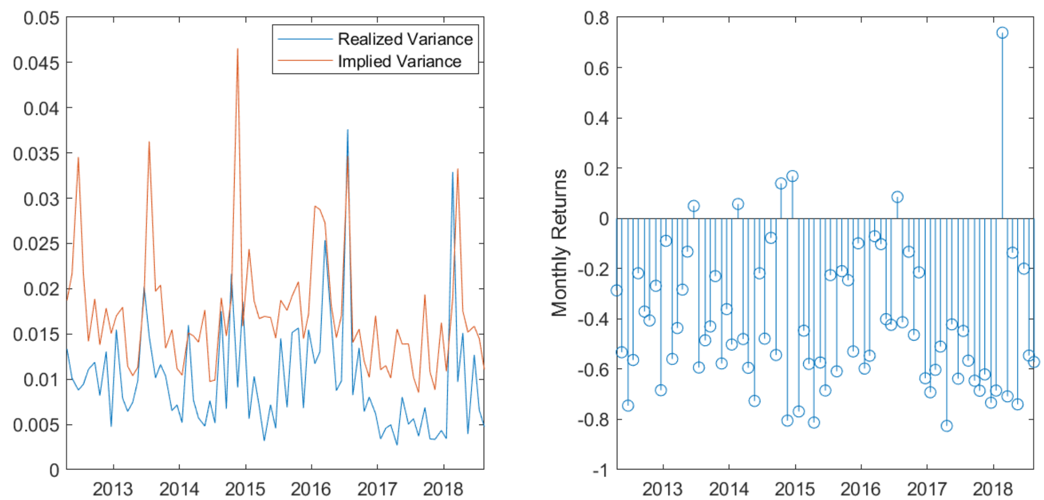

Fig. 2. Credit variance risk premiums

The left graph depicts the monthly realized variances $RV_{t,T}$ and the implied variances $IV_{t,T}$ constructed from CDX North America Investment Grade index options. The right graph shows the corresponding returns which are defined as $RV_{t,T}/IV_{t,T} - 1$. Each month the return is computed such that T corresponds to the expiry date of the Investment Grade index options.

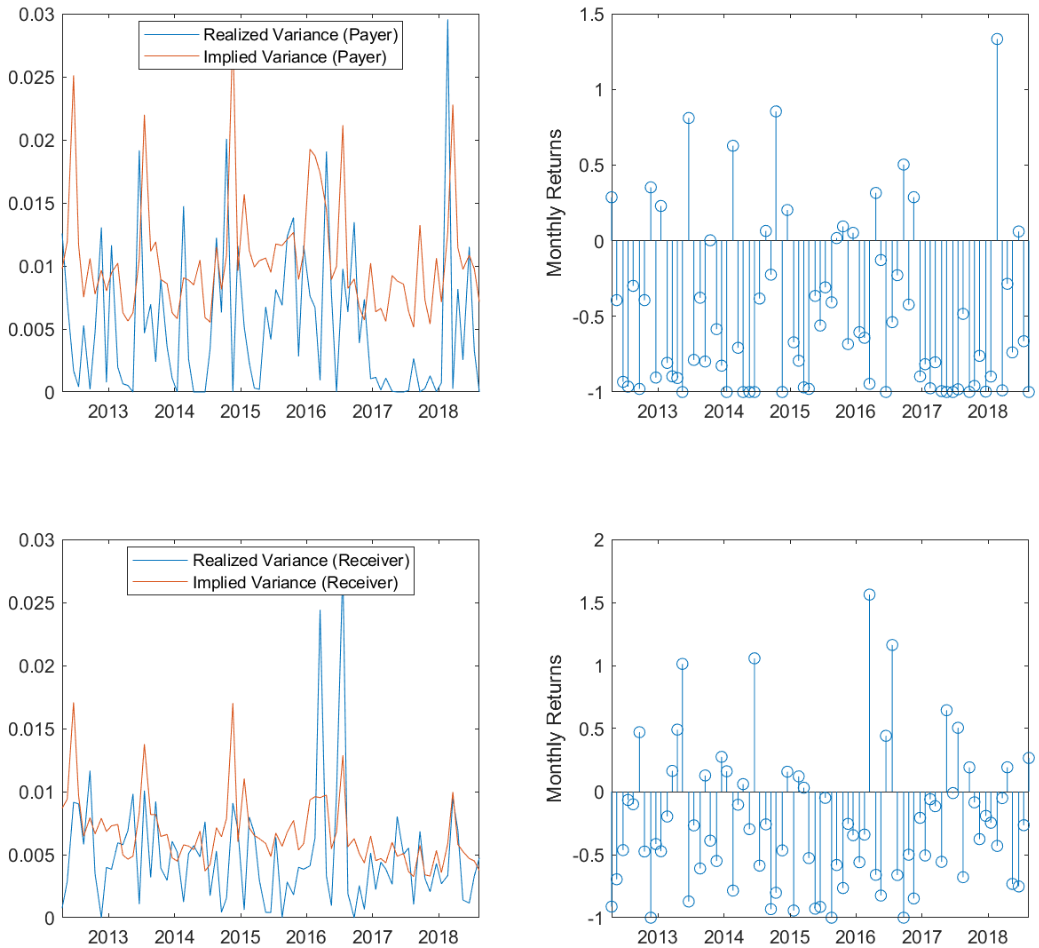

Fig. 3. Realized versus implied characteristics for payer and receiver credit variance risk swaps

The top left graph depicts the monthly realized payer-variances and their respective implied variances. The top right graph shows the corresponding returns which are defined by the barriers $B_d = 0$ and $B_u = \kappa^a_{t_0,T}$. Each month the return is computed such that T corresponds to the expiry date of the CDX North America Investment Grade index options. The bottom left and right graphs depict receiver variances where $B_d = \kappa^a_{t_0,T}$ and $B_u = \infty$.

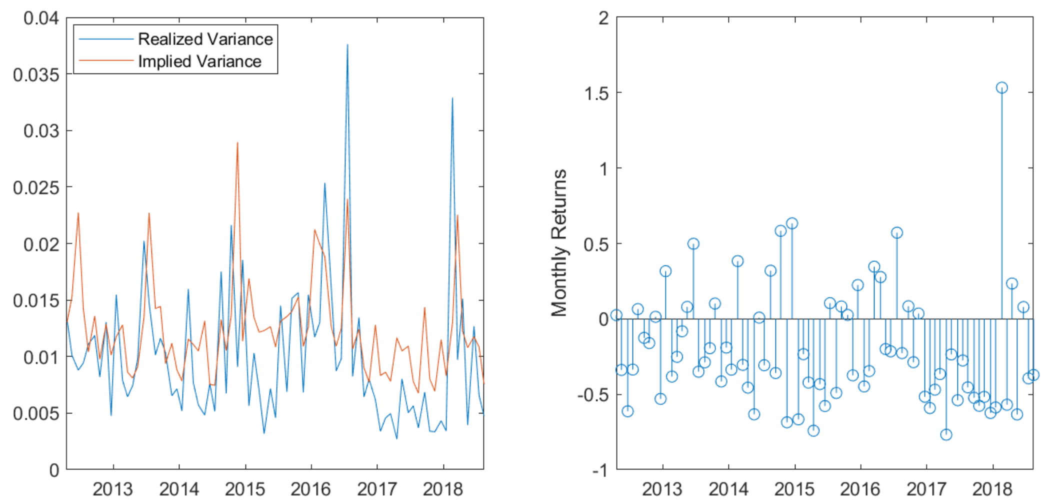

Fig. 4. Credit variance risk premiums from bid prices
The left graph depicts the monthly realized variances $RV_{t,T}$ and the implied variances $IV_{t,T}$ constructed from CDX North America Investment Grade index options. The right graph shows the corresponding returns which are defined as $RV_{t,T}/IV_{t,T} - 1$. Estimation of $IV_{t,T}$ is based on bid swaption prices to account for transaction costs. Each month the return is computed such that T corresponds to the expiry date of the Investment Grade index options.