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Counterparty Credit Risk and Derivatives Pricing

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Abstract

We derive a model with qualitative implications for options pricing under counterparty credit risk and provide empirical evidence using the data from the Hong Kong derivatives market during 2005-2014. We find that the log-price difference between a derivative warrant with counterparty credit risk and an otherwise identical option without counterparty credit risk is significantly and negatively associated with the credit default swap spread on the warrant issuer. We also find that the prices of out-of-the-money put warrants are more sensitive to credit risk than those of other warrants. Our results show counterparty credit risk matters for derivative pricing.

JEL Classification: G13

Keywords: Counterparty credit risk; Mitigating mechanism; Options pricing with vulnerability; Derivative warrants

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1. Introduction

Counterparty credit risk refers to the risk that a counterparty will not pay up as obligated in a contract. In recent years, counterparty credit risk has become a prominent risk for market participants. In 2007-2008, many financial institutions all over the world suffered large and unexpected losses from mortgage-backed securities that culminated in the global credit crisis. Fears of systemic default were widespread shortly after the bankruptcy of Lehman Brothers in September 2008. European financial institutions' large holdings of deteriorating sovereign debt further exacerbated their solvency problems during the European sovereign debt crisis in the late 2012.

The effect of counterparty credit risk on derivative pricing has been thoroughly studied in theoretical models where such derivatives are known as vulnerable derivatives. Earlier models include the options pricing models of Johnson and Stulz (1987), Hull and White (1995), Jarrow and Turnbull (1995), and Klein (1996). Pricing implications are derived under the then-popular assumption that the underlying value follows a geometric Brownian motion process. In particular, independence is assumed for the credit event and the underlying value of the options. More recently, the literature has expanded into counterparty credit risk on other derivatives.[1] However, despite the importance of counterparty credit risk in the financial markets, there are few empirical studies on its pricing in derivative securities. Earlier studies focus almost exclusively on the interest rate swap market. These studies typically find that the effect of counterparty credit risk on the swap rate in interest rate swaps is extremely small. Later studies extend to currency swaps and credit default swaps (CDS). Again, these limited studies find that counterparty credit risk is priced, but the magnitude is vanishingly small.[2] One key reason that these studies find very limited

[1] For example, Cooper and Mello (1991), Sorensen and Bollier (1994), Duffie and Huang (1996), Duffie and Singleton (1997), Jarrow and Yu (2001), Liu, Longstaff, and Mandell (2006), and Yu (2007).

[2] A partial list of empirical studies on the effects of counterparty credit risk on interest rate swaps includes Litzenberger (1992), Sun, Sundarensan, and Wang (1993), Minton (1997), Eom, Subrahmanyam, and Uno (2000, 2002), and Bomfim (2002). Cossin and Pirotte (1997) examine both currency swaps and interest rate swaps. Arora, Gandhi, and Longstaff (2012) examine how the credit risk of CDS dealers affects the CDS spreads they quote. Cserna, Levy, and Wiener (2013) examine the pricing of counterparty credit

roles for counterparty credit risk in determining the prices of derivative securities, even in crisis periods, is related to the credit risk mitigating mechanisms required for over-the-counter (OTC) transactions such as collateral and netting. Collateral partially reduces credit risk, or at least transforms the credit risk to other types of risk, such as market risk or liquidity risk. The netting mechanism ensures that, in case one of the counterparties involved in a transaction defaults, all contracts between the counterparties are aggregated to give a net amount. This mechanism reduces counterparty credit risk and makes the actual credit risk involved in the transactions difficult to measure.

To obtain evidence for the effect of counterparty credit risk on options pricing, we use derivative warrants and options data from the Hong Kong market. The call and put derivative warrants traded in Hong Kong resemble the usual call and put options traded in the US and elsewhere, except that they can be issued, i.e., sold short, only by certain financial institutions approved by regulators.[3] Several key features of Hong Kong derivative warrants and options data make them well suited, though not perfect, for examining the effects of counterparty credit risk on options pricing. The derivative warrants and options in our sample are both traded on the Hong Kong Stock Exchange (HKEx). Exchange-traded options bear virtually no credit risk because margins are required for writing options and they are settled through a central clearing house. In contrast, derivative warrants are subject to the credit risk of their issuers, who are not required to put up collateral against the warrants they issue, unlike OTC derivatives that requires collateral. Derivative warrants are option-type derivatives, where the issuer assumes liability for the transaction. This makes the impact of credit risk on pricing easier to detect, unlike the case of forward-type derivatives, such as interest rate swaps and CDS, where counterparties might assume liability such that it cancels out to a large extent. In our sample, a large number of

risk in exchange-traded notes, which are unsecured structured products issued by financial institutions, but they find only weak evidence that counterparty credit risk is priced.

[3]Derivative warrants are also traded in Germany, Switzerland, Italy, UK, Australia, Singapore, Korea, and several other countries under different names. Derivative warrant is the term used in Hong Kong. The Hong Kong derivative warrant market was the largest in the world in terms of trading volume in 2007-2009 and 2011-2014.

matched pairs of derivative warrants and options with the same contract specifications are available. The use of derivative warrant-option pairs means that our analyses need not rely on specific options pricing models, which can suffer from model specification errors. It also overcomes the need to round up all possible explanatory variables that can affect the prices of derivative warrants.

More specifically, we use the derivative warrants and options written on the Hang Seng Index (HSI) during the period 2005-2014. More than 20 major international investment banks issue warrants on the HSI. All of them also issue their own bonds/debt, and there is active trading of CDS on these banks. We use their CDS spread as a measure of credit risk and examine its effect on the pricing of the warrants they issue relative to the pricing of the options with the same strike price and maturity. The sample period covers both relatively quiet periods and two episodes of financial crisis, the US subprime debt crisis of 2008 and the European sovereign debt crisis of 2011-2012, in which the credit quality of US and European financial institutions deteriorated. The variations in the counterparty credit risk and derivative warrant prices enable identifying their relation. Our empirical results show that counterparty credit risk has a significant impact on the pricing of derivative warrants, controlling for other factors that can affect warrant prices. The relation between the CDS spreads of issuers and the prices of derivative warrants is economically significant. A one percentage point increase in the CDS spread leads to a 1%-1.1% decrease in the price of the derivative warrant.

Our empirical analyses are guided by a simple model that has a minimal parametric structure and yet is rich enough to yield qualitative implications suitable for empirical examination. In particular, we introduce the dependence between the underlying value and the default event of the warrant issuer. Earlier models of vulnerable options, for example, that of Johnson and Stulz (1987), assume independence. The independence assumption fares poorly with the data. During the two financial crises, the HSI plunged, while the default intensity rose among all warrant issuers. The negative association between the underlying value and the default intensity implies that put warrants will lose more value than call warrants, each relative to their options counterparts. Panel A of Fig. 1 plots the average log-price difference between warrants and options, where warrants were issued by Lehman Brothers, and the options are chosen to best match the warrants. The plots are made for puts and calls separately from the beginning of 2008 to the bankruptcy of Lehman Brothers. Panel B of Fig. 1 shows the corresponding five-year CDS spread of Lehman Brothers. The figure shows that the prices of put warrants relative to the prices of put options moved inversely with the CDS spread, especially in the first segment of this period, while the prices of call warrants relative to the prices of call options remained relatively stable.[4] The intuition is straightforward. When the underlying asset suffers a big loss, put options provide protection that is valuable, while call options are out of the money with limited value. If an issuer of warrants defaults with a higher probability when the underlying value declines, the protection that put warrants promise to offer becomes much less trustworthy, so its value declines. The value of call warrants also declines but not as much because they are not valuable to begin with even without credit concerns. The intuition is verified in our model under very mild technical conditions. The pattern observed for warrants issued by Lehman Brothers is also verified in our empirical work for other warrants issuers. In fact, our data support a more delicate implication of the model that out-of-the-money put warrants are more sensitive to counterparty credit risk than in-the-money put warrants.

Figure 1 here

The paper contributes to the literature in several aspects. First, we show an economically and statistically significant effect of counterparty credit risk on derivative prices, thus filling a void in the literature. This verifies earlier theories suggesting that counterparty credit risk has an impact on vulnerable derivatives. We accomplish this by exploiting the difference in credit risk mitigating mechanism between otherwise similar derivative warrants

[4] The large fluctuation in both the relative put prices and CDS spread during mid-March was caused by the fall of Bear Stearns. "Market analysts suggested that Lehman Brothers would be the next major investment bank to fall" (quote from Wikipedia, https://en.wikipedia.org/wiki/Lehman_Brothers).

and options. Second, we abolish the independence assumption made in earlier literature for the underlying value and the default of the derivative issuer and derive implications on the difference in the effect of counterparty credit risk on vulnerable options between puts and calls. The implications, and their extensions, are empirically verified in this paper. Third, we extend the study on the derivative warrants market.[5] Besides liquidity, which is found to be relevant for derivative warrants pricing, this study adds counterparty credit risk and a measure of retail investors' lottery-like trading behavior as extra factors.

The remainder of this paper proceeds as follows. Section 2 presents a simple model with qualitative implications to be tested in later sections. Section 3 provides a brief introduction to the derivative warrants and options markets in Hong Kong and describes our data. Section 4 examines the effects of the credit risk of derivative warrant issuers on the price of the derivative warrants they issue. Section 5 presents several robustness checks of the main results. Finally, Section 6 sets forth our conclusions.

2. A theoretical framework

Several factors can influence the prices of derivatives. Since the main purpose of this paper is to show empirically the influence of counterparty credit risk on the pricing of derivatives, we first present a simple pricing model of vulnerable options, which focuses on the credit risk only, as in the literature. We then discuss other potential factors and their joint effects on the pricing of derivatives.

[5]There are other studies of derivative warrants in the Hong Kong market, but they are unrelated to counterparty credit risk. Duan and Yan (1999) use a semi-parametric approach to price derivative warrants that substantially improves upon the Black–Scholes (1973) model. Chan and Wei (2001), Chen and Wu (2001), and Draper, Mak, and Tang (2001) focus on the effect of introducing derivative warrants on the price and trading volume of underlying securities. Chow, Li, and Liu (2009) examine the trading records of market makers on the Hong Kong derivative warrants market to understand their inventory management. Li and Zhang (2011) show that price differences between derivative warrants and options arise from their liquidity differences. Fung and Zeng (2012) suggest that the implied volatility from derivative warrants provides an unbiased forecast of the future realized volatility of the underlying asset.

2.1. A simple model with qualitative implications

For ease of exposition, vulnerable options will be called (derivative) warrants in this paper. The defining property of warrants here is that their buyers/holders face counterparty credit risk. The model developed here does not describe warrants per se but rather the difference between warrants and otherwise identical options. That way, it makes minimal assumptions on the parametric structure but is rich enough to generate implications testable using available data.[6]

Suppose the value of the underlying asset and the event that a warrant seller defaults follow a joint jump-diffusion model. Let $W^c(t,T,K)$ and $W^p(t,T,K)$ be the prices of a call and a put warrant, respectively, with strike price K and time to expiration $T-t$. Let $O^c(t,T,K)$ and $O^p(t,T,K)$ be the prices of the otherwise identical default-free options. Theoretically speaking,

$$\begin{aligned} O^c(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(S_T-K)^+], && (1)\\ O^p(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(K-S_T)^+], && (2)\\ W^c(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(S_T-K)^+(1_{(\eta>T)}+v1_{(\eta\le T)})], && (3)\\ W^p(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(K-S_T)^+(1_{(\eta>T)}+v1_{(\eta\le T)})], && (4) \end{aligned}$$

where r is the risk-free rate; $\tilde{E}_t$ is the expectation under a risk-neutral measure conditional on the information set at time t; $a^+ = \max(a,0)$; η is the time when the seller of the warrant becomes insolvent and triggers a credit event, in which the issuer pays a fraction

[6] There are two reasons why only a simple model with qualitative implications on the differences between warrants and options is attempted here. The first is that options pricing literature has not settled on a model that can accurately price options, even without counterparty credit risk. Evidence suggests that sophisticated options pricing models with stochastic volatility and jumps in the underlying asset (Bates, 2000; Pan, 2002) and with jumps in both underlying asset and asset volatility (Eraker, 2004) cannot fit the cross-section of options data satisfactorily. Evidence also shows that the class of popular affine jump-diffusion models suffers from misspecification errors in general (see for example, Jones, 2003; Christoffersen, Jacobs, and Mimouni, 2010; and Li and Zhang, 2013). Adding counterparty credit risk to such models is doomed to fail when real data are used due to the problems with the options pricing part, even if the credit risk part is perfect. The second reason is that, besides counterparty credit risk, other nontrivial factors influence warrants pricing. Some of them are not suitable for modeling, as they can involve irrational behavior.

v, known as the recovery rate, of its obligation; and $1_{(\eta > T)}$ is the indication function for the seller not becoming insolvent before T. Rewrite $W^c(t, T, K)$ as

$$\begin{aligned} W^c(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(S_T - K)^+ - e^{-r(T-t)}(S_T - K)^+(1-v)1_{(\eta \leq T)}] \\ &= O^c(t,T,K) - A^c(t,T,K) \quad (5) \\ &= O^c(t,T,K)[1 - B^c(t,T,K)\tilde{E}_t(Y_T)], \quad (6) \end{aligned}$$

where

$$\begin{aligned} Y_T &= (1-v)1_{(\eta \leq T)}, \quad (7) \\ A^c(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(S_T - K)^+ Y_T], \quad (8) \\ B^c(t,T,K) &= \frac{\tilde{E}_t[e^{-r(T-t)}(S_T - K)^+ Y_T]}{\tilde{E}_t[e^{-r(T-t)}(S_T - K)^+]\tilde{E}_t[Y_T]}. \quad (9) \end{aligned}$$

Likewise,

$$\begin{aligned} W^p(t,T,K) &= O^p(t,T,K) - A^p(t,T,K) \quad (10) \\ &= O^p(t,T,K)[1 - B^p(t,T,K)\tilde{E}_t(Y_T)], \quad (11) \end{aligned}$$

with

$$\begin{aligned} A^p(t,T,K) &= \tilde{E}_t[e^{-r(T-t)}(K - S_T)^+ Y_T], \quad (12) \\ B^p(t,T,K) &= \frac{\tilde{E}_t[e^{-r(T-t)}(K - S_T)^+ Y_T]}{\tilde{E}_t[e^{-r(T-t)}(K - S_T)^+]\tilde{E}_t[Y_T]}. \quad (13) \end{aligned}$$

In general, $A^c(t,T,K)$, $B^c(t,T,K)$, $A^p(t,T,K)$, and $B^p(t,T,K)$ are functions of strike price K, the time to expiration $T - t$, and whatever state variables that enter the conditional expectation $\tilde{E}$.

Let $D^c(t,T,K) = W^c(t,T,K) - O^c(t,T,K)$, $D^p(t,T,K) = W^p(t,T,K) - O^p(t,T,K)$, $d^c(t,T,K) = \log[W^c(t,T,K)/O^c(t,T,K)]$, and $d^p(t,T,K) = \log[W^p(t,T,K)/O^p(t,T,K)]$. The price differences between warrants and default-free options are

$$\begin{aligned} D^c(t,T,K) &= -A^c(t,T,K) < 0, \quad (14) \\ D^p(t,T,K) &= -A^p(t,T,K) < 0, \quad (15) \\ d^c(t,T,K) &= \log[1 - B^c(t,T,K)\tilde{E}_t(Y_T)] \approx -B^c(t,T,K)\tilde{E}_t(Y_T) < 0, \quad (16) \\ d^p(t,T,K) &= \log[1 - B^p(t,T,K)\tilde{E}_t(Y_T)] \approx -B^p(t,T,K)\tilde{E}_t(Y_T) < 0. \quad (17) \end{aligned}$$

The price differences are negative because all of the multiplicative terms in $A^c(t,T,K)$, $A^p(t,T,K)$, $B^c(t,T,K)$, and $B^p(t,T,K)$ are positive, and $\tilde{E}_t(Y_T) > 0$ as assumed for warrants. Obviously the prices of warrants, both calls and puts, carry a vulnerability discount, which is a counterparty credit discount. The discount is related to the risk-adjusted probability of default status and the loss given default, Y_T. More qualitative statements can be made in terms of the difference between calls and puts and the effect of moneyness.

First, if S_T and Y_T are independent, then $A^c(t,T,K) = O^c(t,T,K)\tilde{E}_t(Y_T)$, $A^p(t,T,K) = O^p(t,T,K)\tilde{E}_t(Y_T)$, and $B^c(t,T,K)$ and $B^p(t,T,K)$ are both equal to one, so the log-price differences for both calls and puts are equal to $\log[1-\tilde{E}_t(Y_T)] \approx -\tilde{E}_t(Y_T)$, which, when further assuming the independence between default and recovery rate, is equal to $\tilde{E}_t(1-v)\cdot\tilde{P}(\eta \leq T)$, i.e., the product of the risk-neutral expected loss given default and the risk-neutral default probability.

Suppose S_T and Y_T are not independent. We say S_T and Y_T are strictly positively quadrant-dependent under a probability P if $P(S_T < s, Y_T < y) > P(S_T < s)P(Y_T < y)$ for all (s,y). Similarly, S_T and Y_T are said to be negatively quadrant-dependent if the probability inequality is reversed.

Positive (negative) quadrant dependence between S_T and Y_T implies that

$$\mathrm{Cov}_t(f(S_T), g(Y_T)) > 0 \quad (< 0) \tag{18}$$

for all increasing functions f and g, where Cov_t is the time t conditional covariance under probability P. Since $(S_T-K)^+$ is increasing in S_T for calls and $(K-S_T)^+$ is decreasing in S_T for puts, Proposition 1 follows immediately.

Proposition 1. *(i) If S_T and Y_T are strictly positively quadrant-dependent under the risk-neutral probability, then $A^c(t,T,K) > O^c(t,T,K)\tilde{E}_t(Y_T)$, $A^p(t,T,K) < O^p(t,T,K)\tilde{E}_t(Y_T)$, $B^c(t,T,K) > 1$, and $B^p(t,T,K) < 1$ so that calls have larger vulnerability discounts than puts, other things being equal. (ii) If S_T and Y_T are strictly negatively quadrant-dependent under the risk-neutral probability, then $A^c(t,T,K) < O^c(t,T,K)\tilde{E}_t(Y_T)$, and*

$A^p(t,T,K) > O^p(t,T,K)\tilde{E}_t(Y_T)$, $B^c(t,T,K) < 1$, and $B^p(t,T,K) > 1$ so that puts have larger vulnerability discounts than calls, other things being equal.

The intuition behind the proposition is clear. Default-free calls gain more than puts when the underlying value is high. If the underlying value and default are positively quadrant-dependent, the fact that call writers may default renders the vulnerable calls less valuable. Similarly, default-free puts gain more than calls when the underlying value is low. If the underlying value and default are negatively quadrant-dependent, the fact that put writers may default reduces the value of vulnerable puts. The situation in (ii) is more relevant for the empirical results of the paper. In the example of Lehman Brothers, a prestige investment bank at the time, S_T is the HSI, an index for large-cap stocks traded in Hong Kong, or stocks of large companies. The underlying asset price and the risk-neutral probability of default multiplied by the loss given default are obviously negatively quadrant-dependent. Hence we see that puts are more discounted than calls. We will show in the empirical section that this is also true for warrants written on the HSI issued by all of the other investment banks.

Since the deviation from one for the $B(t,T,K)$ function comes from the dependence between the underlying value and the warrant writer's credit risk, it is conceivable that for the same type of warrants, i.e., calls or puts, the valuation can be different for warrant writers with different degrees of dependence. For two warrant writers, coded as 1 and 2, with the same probability of default $P(Y_{1T} < y) = P(Y_{2T} < y)$ for all y, we say that the quadrant dependence between one's credit risk and the underlying value is strictly more positive for warrant writer 1 than for warrant writer 2, if $P(S_T < s, Y_{1T} < y) > P(S_T < s, Y_{2T} < y)$ for all (s, y). Note that this does not require the credit risk of either warrant writer to have positive quadrant dependence with the underlying value. Since it is relative between the two warrant writers, we do not need to separately define a more negative quadrant dependence.

That warrant writer 1 has a strictly more positive quadrant dependence between its credit risk and the underlying value than warrant writer 2 implies that $P((S_T - K)^+ < s, Y_{1T} < y) > P((S_T - K)^+ < s, Y_{2T} < y)$ and $P((K - S_T)^+ < s, Y_{1T} < y) < P((K - S_T)^+ < s, Y_{2T} < y)$ for all (s, y). This immediately translates to inequalities in terms of expectations. Therefore, we have Proposition 2.

Proposition 2. *Suppose that warrant writer 1 has a strictly more positive quadrant dependence between its credit risk and the underlying value than warrant writer 2 under the risk-neutral probability. Then, (i)* $A_1^c(t,T,K) > A_2^c(t,T,K)$ *and* $A_1^p(t,T,K) < A_2^p(t,T,K)$*; and (ii)* $B_1^c(t,T,K) > B_2^c(t,T,K)$ *and* $B_1^p(t,T,K) < B_2^p(t,T,K)$.

The next result pertains to the effect of moneyness on the vulnerability discount, holding other factors constant. For notational simplicity, assume $r = 0$ without loss of generality. For absolute price differences, we note that

$$\frac{\partial A^c(t,T,K)}{\partial K} = -\tilde{E}_t[1_{(K,\infty)}(S_T)Y_T] < 0 \tag{19}$$

$$\frac{\partial A^p(t,T,K)}{\partial K} = \tilde{E}_t[1_{(0,K)}(S_T)Y_T] > 0. \tag{20}$$

So the vulnerability discount in terms of the absolute price differences increases as an option, be it a call or a put, becomes more in the money. For proportional price differences,

$$\begin{aligned}\frac{\partial B^c(t,T,K)}{\partial K} &= \frac{\tilde{E}_t[1_{(K,\infty)}(S_T)]}{\tilde{E}_t[(S_T-K)^+]\tilde{E}_t[Y_T]} \cdot \left[\frac{\tilde{E}_t[(S_T-K)^+Y_T]}{\tilde{E}_t[(S_T-K)^+]} - \frac{\tilde{E}_t[1_{(K,\infty)}(S_T)Y_T]}{\tilde{E}_t[1_{(K,\infty)}(S_T)]}\right] \\ &= \frac{\tilde{E}_t[1_{(K,\infty)}(S_T)]}{\tilde{E}_t[(S_T-K)^+]\tilde{E}_t[Y_T]} \cdot \tilde{E}_t[f(S_T)Y_T], \end{aligned} \tag{21}$$

where

$$f(S_T) = \frac{(S_T-K)^+}{\tilde{E}_t[(S_T-K)^+]} - \frac{1_{(K,\infty)}(S_T)}{\tilde{E}_t[1_{(K,\infty)}(S_T)]}, \tag{22}$$

with $f'(S_T) \geq 0$ and $\tilde{E}_t[f(S_T)] = 0$. Therefore, if S_T and Y_T are positively quadrant-dependent, then $\tilde{E}_t[f(S_T)Y_T] > \tilde{E}_t[f(S_T)]\tilde{E}_t[Y_T] = 0$, so $\frac{\partial B^c(t,T,K)}{\partial K} > 0$, and if S_T and Y_T are negatively quadrant-dependent, then $\frac{\partial B^c(t,T,K)}{\partial K} < 0$.

Similarly, for put warrants,

$$\frac{\partial B^p(t,T,K)}{\partial K} = \frac{\tilde{E}_t[1_{(0,K)}(S_T)]}{\tilde{E}_t[(K-S_T)^+]\tilde{E}_t[Y_T]} \cdot \tilde{E}_t[g(S_T)Y_T], \tag{23}$$

where

$$g(S_T) = \frac{1_{(0,K)}(S_T)}{\tilde{E}_t[1_{(0,K)}(S_T)]} - \frac{(K - S_T)^+}{\tilde{E}_t[(K - S_T)^+]}, \tag{24}$$

with $g'(S_T) \geq 0$ and $\tilde{E}_t[g(S_T)] = 0$. Therefore, $\frac{\partial B^p(t,T,K)}{\partial K} > 0$ if S_T and Y_T are positively quadrant-dependent, and $\frac{\partial B^p(t,T,K)}{\partial K} < 0$ if S_T and Y_T are negatively quadrant-dependent. We summarize the above results in Proposition 3.

Proposition 3. *(i)* $\frac{\partial A^c(t,T,K)}{\partial K} < 0$, $\frac{\partial A^p(t,T,K)}{\partial K} > 0$*; that is, the more in the money a warrant is, be it a call or a put, the larger the absolute discount. (ii) If* S_T *and* Y_T *are strictly positively quadrant-dependent, then* $\frac{\partial B^c(t,T,K)}{\partial K} > 0$ *and* $\frac{\partial B^p(t,T,K)}{\partial K} > 0$*. (iii) If* S_T *and* Y_T *are strictly negatively quadrant-dependent, then* $\frac{\partial B^c(t,T,K)}{\partial K} < 0$ *and* $\frac{\partial B^p(t,T,K)}{\partial K} < 0$*.*

Proposition 3 (i) states that the more in the money a warrant is, the greater the absolute vulnerability discount, whether the warrant is a call or a put. This is intuitive. Proposition 3 (ii) and (iii), however, state that the proportional discount depends on whether the dependence between the underlying value and the credit risk is positive or negative and is opposite for calls and puts. To understand it, let's focus on the case in which the underlying value and the credit risk are negatively quadrant-dependent. With a smaller K, the put payoff is nonzero only when S_T is lower, while Y_T takes on a higher value in the conditional expectation in the numerator of Eq. (13), and B^p is larger as a result. In contrast, with a larger K, the call payoff is nonzero only when S_T is higher, and Y_T takes on a lower value in the conditional expectation in the numerator of Eq. (9), and B^c is smaller.

These implications can all be examined in the later empirical study to various extent. It should be pointed out that the implications derived in this subsection are unique to counterparty credit risk. These implications are not associated with other factors that could potentially affect the prices of derivative warrants.

2.2. Implications for the empirical specifications

Suppose the warrant issuer also sells a zero-coupon bond maturing at the same time as the warrant, and the bond is pari passu with the warrant. The value of the bond with the face value normalized to one equals $e^{-r(T-t)}[1-\tilde{E}_t(Y_T)]$. The yield to maturity of the bond is $r-[\log(1-\tilde{E}_t(Y_T))]/(T-t)$. The yield spread is then $-[\log(1-\tilde{E}_t(Y_T))]/(T-t)$, approximated to $\tilde{E}_t(Y_T)/(T-t)$. The annualized CDS spread, if written on the zero-coupon bond, is theoretically the same as the yield spread. The equations for the proportional price difference between warrants and options, Eq. (16) and Eq. (17), can then be written as

$$d^c(t,T,K) \approx -B^c(t,T,K)\cdot \text{CDS}\tau, \tag{25}$$

$$d^p(t,T,K) \approx -B^p(t,T,K)\cdot \text{CDS}\tau, \tag{26}$$

where the unannualized CDS spread, $\text{CDS}\tau$, is the premium paid over $\tau = T-t$ period for the protection of the bond issued by the warrant issuer. An important feature of the analysis is that, when counterparty credit risk is the only factor in the warrant pricing, the proportional price difference between a warrant and an option in a pair, up to the first-order approximation, depends on the strike price, the time to expiration, and whatever state variables only through the slope coefficient of $\text{CDS}\tau$. We can use observable CDS spreads on the warrant issuers as a proxy for $\tilde{E}_t(Y_T)/(T-t)$ to conduct empirical analysis, although, technically, the two differ slightly in many aspects.[7]

Since $B^c(t,T,K)$ and $B^p(t,T,K)$ are both equal to one if S_T and Y_T are independent, the slope coefficient β_1 must be equal to -1 in a benchmark regression of the type $d(t,T,K)=\beta_1\text{CDS}\tau+\varepsilon$. This simple case serves to provide fresh evidence of the existence of the vulnerability discount in derivative pricing given that the literature has failed to demonstrate its economic significance empirically as mentioned in Introduction.

If S_T and Y_T are negatively quadrant-dependent under the risk-neutral probability, Proposition 1 implies that when a simple regression of the type $d(t,T,K)=\beta_1\text{CDS}\tau+\varepsilon$ is applied to the call sample and the put sample separately, the slope coefficient for the call sample will be less negative than -1, while that for the put sample will be more negative

[7]For example, in CDS trading, the settlement is at default upon the conclusion of CDS auction a couple of weeks later, not at the CDS maturity. For derivative warrants, the defaulted seller of warrants will pay a fraction of promised claims valued at the expiration day of warrants. The assumption of the recovery rate as in Eq. (3) and Eq. (4) is consistent with the practice in the Hong Kong derivative warrants market but not with that of the CDS market.

than -1. Alternatively, when the simple regression is applied to the whole sample, but with the additional cross-product term $1^p \cdot \text{CDS}\mathcal{T}$, where 1^p is the dummy variable for puts, the coefficient of $\text{CDS}\mathcal{T}$ is less negative than -1, and the coefficient of $1^p \cdot \text{CDS}\mathcal{T}$ is negative.

In general, the slope coefficient of $\text{CDS}\mathcal{T}$ is a function of the strike price, time to expiration, and the state variables: $\beta_1(t, T, K, X_t)$ where X_t represents the vector of state variables. We examine this by assuming a linear functional form as the first approximation in the robustness check section and through semi-nonparametric estimation without assuming any functional form.

The notion of quadrant dependence between S_T and Y_T in the propositions is stronger than correlation but the weakest among several other dependence notions. Checking quadrant dependence empirically is difficult, however, as it requires the knowledge of joint and marginal distributions of (S_T, Y_T) or the sign of $\text{Cov}_t(f(S_T), g(Y_t))$ for all increasing functions f and g. But fortunately, the condition regarding quadrant dependence is sufficient rather than necessary, for the propositions. More specifically,

- for Proposition 1 (ii) to hold, we need $\text{Cov}_t((S_T - K)^+, Y_T) < 0$ and $\text{Cov}_t((K - S_T)^+, Y_T) > 0$ for relevant Ks only,
- for $B_1^p(t, T, K) < B_2^p(t, T, K)$ in Proposition 2 (ii) to hold, we need $\text{Cov}_t((K - S_{1T})^+, Y_T) < \text{Cov}_t((K - S_{2T})^+, Y_T)$ for relevant Ks only,
- and for $\frac{\partial B^p(t,T,K)}{\partial K} < 0$ in Proposition 3 (iii) to hold, we need $\text{Cov}_t(g(S_T), Y_T) < 0$ for relevant Ks only, where $g(\cdot)$ is defined in Eq. (24).

Another issue pertains to the difference in these covariances between risk-neutral probability in the model and physical probability in empirical work. Although, theoretically, the covariances can differ between the two probabilities, many empirical studies in various similar contexts assume that they are the same simply because there is not enough information in the data to identify risk premiums associated with all state variables, for example, Pan (2002) and Broadie, Chernov, and Johannes (2007). In our case, the requirement for linking the covariances under the two probabilities is weaker. The covariances under the two probabilities do not have to be the same. As long as the ordering of the covariances across different warrant issuers remains the same for the two probabilities, Proposition 2 can be restated in terms of the physical probability. Since the warrant issuers are all major international investment banks and there is no specific reason, a priori, to assign a different risk premium per unit of risk associated with the covariance to one bank from others, it is conceivable that the orderings of the conditional covariances among all the warrant issuers are the same under both risk-neutral and physical probabilities. In the empirical work below, this is assumed.

2.3. Other factors influencing warrant prices

In additional to counterparty credit risk, derivative warrants traded in the Hong Kong market and elsewhere are priced differently than options of the same strike price and maturity for two other reasons. One is that they have difference levels of liquidity, and the other pertains to the overpricing caused by retail investors' lottery-like trading behavior. We describe them in turn.

The difference in liquidity between derivative warrants and options stems from their minimum trading sizes, as shown by Li and Zhang (2011). The exchange stipulates that a round lot of options on stocks is the same as or more than a round lot of the underlying stocks, while a round lot of derivative warrants, determined by the issuer, is typically only one-tenth of a round lot of the underlying stocks. The difference in trading sizes between derivative warrants and options on stock indexes is even greater. This creates a clientele effect. Options traders tend to be either institutional traders or wealthy, sophisticated individual traders. Derivative warrants traders tend to be small, unsophisticated traders with short holding periods. The HKEx also requires each issuer to appoint a liquidity provider to input bid and ask prices into the trading system and be prepared to trade with other traders. This further improves the liquidity of the derivative warrants market. Derivative warrants have a much larger trading volume and turnover than options; they also have a much lower Amihud illiquidity measure than options, except for out-of-money, short-term derivative warrants.[8]

The small trading size of derivative warrants with high liquidity attracts small retail investors. Some of these investors exhibit trading behavior that is difficult to justify. Since derivative warrants can only be issued by institutions that have permission from regulators and investors without such permit cannot sell them short, the prices of derivative warrants can be biased upward. Although this is widely believed to be the case by market pundits and mentioned in various media sources, the degree to which it is true has not been rigourously shown in academic studies. A comprehensive study of this is beyond the scope of our paper, but we devise simple measures of this potential bias in the price difference between derivative warrants and options, as control variables in identifying of the effect of counterparty credit risk. Our measures pertain to the common moneyness of a warrant-option pair and their common time to expiration, which are not expected to have any effect on the price differences between pairs of derivative warrants and options, provided that no bias exists. However, retail investors who pursue a lottery-buying (or skewness preference) trading strategy tend to overpay for those derivative warrants that appear to be cheap. In this sense, short-term, out-of-money derivative warrants are more susceptible to such bias.

Since liquidity and lottery-buying behavior are not the main focus of this paper, we do not formally model them. Instead, we use measures of these potential forces as control variables and focus on our main query about the effect of counterparty credit risk on the pricing of vulnerable derivatives. This is equivalent to assuming that there is a liquidity premium and a skewness-preference premium in the form of

$$\hat{W}(t,T,K) = e^{(\beta_{0t}+\beta_2 \text{LIQ}+\beta_3 \text{MON}+\beta_4 \text{LTE})} W(t,T,K), \tag{27}$$

for call and put warrants. W is the price of a vulnerable option, which differs from an option by the counterparty credit risk discount only, and $\hat{W}$ is the price of a warrant that

[8]In the recent literature of bond pricing including Chun et al. (2017), models with credit risk and liquidity risk have been developed. The situation is much more complicated in the case of derivative warrants because their liquidity differs across issuers for the same option and differs across derivative warrant-option pairs for the same issuer.

accounts for additional liquidity and skewness-preference premiums. LIQ is the measure of liquidity; MON is moneyness, defined as $1 - K/S_t$ for a call and $K/S_t - 1$ for a put; and LTE is the logarithm of time to expiration for individual warrants. In particular, β_2 is a positive coefficient, β_3 and β_4 are negative coefficients, and β_{0t} is a function of state variables. The log-price difference, $\hat{d}(t, T, K) = \log(\hat{W}(t, T, K)/O(t, T, K))$, equals

$$\hat{d}(t, T, K) = \beta_{0t} + \beta_1(t, T, K, X_t)\text{CDS}\tau + \beta_2\text{LIQ} + \beta_3\text{MON} + \beta_4\text{LTE}. \tag{28}$$

This equation is the main focus of our empirical examination.

3. Derivative warrants and options in Hong Kong

3.1. Description of the markets

Trading of derivative warrants and options in Hong Kong is conducted on the HKEx, which is divided into the securities market, the derivatives market, and the base metals market. Stocks and derivative warrants, among others, are traded in the securities market, in which derivative warrants accounted for about 16% of the total trading volume from 2005 to 2014. Futures and options on indexes and individual stocks, interest rate futures, current futures, and gold futures are traded in the derivatives market. The acquisition of the London Metal Exchange in 2012 by HKEx forms its base metals market.

There are two types of warrants in Hong Kong, equity warrants and derivative warrants. In recent years, most warrants traded on the HKEx are derivative warrants. Equity warrants are issued by a listed company and give holders the right to subscribe for equity securities of that company. When these warrants are exercised, the listed company issues new shares to their holders and collects extra capital. Derivative warrants are structured products. They are issued by a third party, usually an investment bank that is unrelated to the issuer of the underlying asset. Both call and put derivative warrants exist. The underlying assets can be a single security or a basket of securities, stock indices, currencies, commodities, or futures contracts. When a call derivative warrant on a single stock is exercised, no new shares of the underlying company are issued. Almost all derivative warrants currently traded in Hong Kong are European style and cash settled. Issuers of derivative warrants include several major US, European, and Australian banks, such as Goldman Sachs, Citigroup, JP Morgan, Lehman Brothers, Société Générale, KBC, Deutsche Bank, BNP Paribas, and Macquarie Bank. Each underlying asset can have multiple issuers that compete with each other to offer popular contract specifications, lower prices, and better liquidity.

Derivative warrants represent issuers' or their guarantors' general contractual obligations. They are not secured on any of the issuers' or guarantors' assets or collateral and rank equally with other general unsecured obligations of the issuers/guarantors. Thus, derivative warrants are subject to the credit risk of issuers or guarantors. The credit risk of the issuer is usually the first risk factor disclosed in the listing document of a derivative warrant. The HKEx issues advisory letters periodically to remind derivative warrant investors of the credit risk associated with derivative warrant issuers and provides information on the credit ratings of issuers on its web site and updates the ratings on a daily basis. One important case regarding the counterparty credit risk of derivative warrant issuers is the collapse of Lehman Brothers.

Since 2001, the HKEx has required that all issuers appoint a liquidity provider to input bid and ask prices into the trading system, either continuously or on request. Some issuers also provide information, such as the average bid-ask spread and the average size of bid and ask quotes of the derivative warrants issued by them, to advertise the quality of their liquidity provision. This requirement has improved the liquidity of the derivative warrants market in Hong Kong, and the market has been ranked the largest in the world in terms of trading volume in recent years. Most warrant issuers act as liquidity providers themselves and become active traders in the market while making the market. In fact, their degree of involvement in trading becomes the best measure of liquidity for a given warrant.

Index options in Hong Kong are European style and settled in cash, while stock options are American style with physical delivery of the underlying assets upon exercise. The contract specifications of the options are set by the exchange. To trade in the options market in Hong Kong, an investor can either open a cash account or a margin account with a broker registered with the HKEx. If the investor maintains a cash account with a broker, he or she can carry long option positions only and is not subject to paying margins. If the investor maintains a margin account with a broker, he or she can take both long and short positions and will be required to pay margin based on the Standard Portfolio Analysis of Risk (SPAN) margin methodology. SPAN is a risk-based portfolio approach for calculating the daily margin requirement developed by the Chicago Mercantile Exchange. It constructs scenarios of futures price movements and volatility changes to estimate the potential losses of the entire portfolio in the following trading day and computes the margin requirement to cover those losses.

3.2. Data sources

We focus on derivative warrants and options written on the HSI. A comparison between derivative warrants and options on the HSI is clean, as they are both European style and cash settled. The HSI is the benchmark index in the Hong Kong stock market, and the derivatives written on it are the most liquid. We refer to derivative warrants on the HSI simply as warrants because the underlying asset is an index and there is no confusion.

The data on warrants and options on the HSI are obtained from the HKEx. The warrants data include daily closing bid and ask prices, trading share volume, dollar volume, and contract specifications, such as maturity and strike price. The options data include intraday bid and ask quotes, daily trading volume, maturity, and strike price. The options market closes at 4:15 pm, and the warrants market closes at 4:00 pm. We select the intraday bid and ask quotes of options closest to 4:00 pm and match them with the closing prices of warrants. We use a sample of warrants and options matched by maturity and strike price so that their prices can be compared.[9] We require both warrants and options to have positive

[9]Warrant issuers can choose the specifications of warrants to issue. However, they tend to issue warrants

daily volumes to mitigate the concern of stale quotes. We remove the observations with option prices less than 0.25% of the HSI level to reduce the large proportional pricing errors from these low-priced options, which account for about 1% of the sample. The closing HSI level is obtained from Yahoo! Finance. The sample period is from January 1, 2005, to December 31, 2014.

We use CDS spreads of warrant issuers to measure their credit risk. A CDS is a derivative security to insure against the default risk of a particular entity. The buyer of the CDS makes periodic payments—known as the CDS spread—to the seller until the end of the life of the CDS or until the default of the entity in which case the buyer has the right to sell the bond issued by the entity for the face value back to the seller. The CDS spread is approximately equal to the excess of the par yield on the bond over the par yield on the risk-free bond with the same maturity. When the credit risk of the underlying entity is high, CDS buyers are willing to pay a high premium, i.e., the CDS spread, to insure against the risk. CDS spreads offer some advantages as a measure of credit risk relative to other measures, such as corporate bond yield spreads. For example, CDS spreads represent more timely market information and are less contaminated by liquidity and tax effects, and CDS contracts are standardized and comparable across firms. The end-of-day average closing bid and ask quotes of CDS spreads are downloaded from Markit.[10] We linearly interpolate or extrapolated senior CDS spreads of available tenors to match the time to expiration of warrants and use them to measure the counterparty credit risk of the corresponding warrants. In Section 5, we also use the senior six-month CDS spreads, the tenor best matched with that of warrants among available CDS spreads, to run the main regressions

with the same specifications as available options. About 25% of HSI warrants cannot be matched with options of the same maturity and strike price, and these are excluded from our sample. Lehman Brothers issued warrants on HSI for only a very brief period in the summer of 2008 without perfectly matched options. As a result, it is not included in the sample.

[10]End-of-day quotes on CDS spreads are made according to either New York time or London time, depending on the individual entity, which gives rise to the time difference between the CDS spreads and prices of warrants and options traded in Hong Kong. We find that the results are essentially the same regardless of whether warrant and option prices are matched with CDS spreads on the same calendar day or with a one-day lag. In the results reported below, two sets of data are matched on the same calendar day.

again as a robustness check. It should be noted that, while the warrants and options on HSI are traded in Hong Kong only, CDSs on the warrant issuers are traded globally. Potential market segmentation can cause the relation between relative warrant prices and CDS spreads not to follow exactly what the model implies.

3.3. Warrants issuers

Table 1 reports the names of issuers and the number of warrants issued in the sample period. There are 21 issuers in the sample. European banks, including Société Générale, KBC, Deutsche Bank, and BNP Paribas, are the most active issuers. Some American and Australian banks, such as Goldman Sachs and Macquarie Bank, are also important issuers in the warrants market. The number of call warrants and that of put warrants are roughly the same. Issuers tend to issue calls and puts with the same strike price and maturity for hedging purposes. In our sample, there are 3,213 different warrants and 78,793 warrant-day observations matched with options.

Table 1 here

Panel A of Fig. 2 shows the time-series plots of the 10th percentile, median, and 90th percentile of the monthly average of six-month CDS spreads in percentage points across warrant issuers. CDS spreads were low and stable from 2005 to the first half of 2007. From the second half of 2007, CDS spreads began to increase. The first spike in the time series corresponds to the collapse of Bear Stearns in early 2008. CDS spreads increased further from the second half of 2008 to early 2009. After a relatively stable period from late 2009 to early 2011, CDS spreads increase again in the second half of 2011 amid the European sovereign debt crisis. After then, CDS spreads began to decrease and stayed at low levels. The cross-sectional differences in CDS spreads were small in 2005-2007 and 2013-2014 and large in 2008-2012, a pattern resembling that of the average CDS spreads. The dispersion of CDS spreads peaked in September 2008, when Lehman Brothers filed for bankruptcy. Panel B of Fig. 2 shows the time-series plots of the average six-month, one-, and two-year

CDS spreads. The term structure of CDS spreads sloped upward for most of the time, except for late 2008 and early 2009 when CDS spreads of both maturities shot up.

Figure 2 here

The time-series mean and standard deviation of the daily six-month CDS spreads for individual issuers are tabulated in Table 2. Some American and Australian banks, such as Morgan Stanley, Merrill Lynch, and Macquarie Bank, were among the banks with the highest CDS spreads during the sample period, whereas HSBC and Rabobank had the lowest CDS spreads. The volatilities of CDS spreads tend to be high for banks with high average CDS spreads. Since there are substantial differences in the level of credit risk, as well as cross-sectional variation across the sample period, as suggested in Fig. 2, we further divide the sample into two subsamples. The high CDS spread sample concerns the period 2008-2012, and the low CDS spread sample concerns the periods 2005-2007 and 2013-2014. The level and volatility of CDS spreads in the high CDS spread sample are substantially higher than those in the low CDS spread sample for all issuers.

Table 2 here

We use the entire sample to estimate unconditional correlations between weekly CDS spread changes and normalized payoffs of calls,

$$\text{CSC(MON)} = \text{Corr}[(S_T/S_t - K/S_t)^+, \text{CDS}_T^{6m} - \text{CDS}_t^{6m}], \tag{29}$$

for each issuer and various strike prices, K, where MON $= 1 - K/S_t$ and CDS^{6m} is the six-month CDS spread. Similarly, we estimate unconditional correlations between weekly CDS spread changes and negative normalized payoffs of puts,

$$\text{CSP(MON)} = \text{Corr}[-(K/S_t - S_T/S_t)^+, \text{CDS}_T^{6m} - \text{CDS}_t^{6m}], \tag{30}$$

where MON $= K/S_t - 1$. The scatter plots of among CSC(MON) and CSP(MON) are shown in Fig. 3. For various values of MON, CSP(MON) is negative for all issuers, and

CSC(MON) is also negative, except for one issuer. This provides supporting evidence for the condition of Proposition 1 (ii). The figure also suggests that CSC(MON) and CSP(MON) of issuers are highly and positively correlated for various pairs of MONs. This indicates that issuers with more negative correlations for a given MON are likely to have more negative correlations for other MONs. Because rankings of correlations among issuers for various values of MON are rather stable, we can separate issuers with different degrees of dependence and test Proposition 2.[11] These correlations tend to be more negative during the high CDS spread period.

Figure 3 here

We also calculate unconditional correlations between weekly CDS spread changes and $f(S_T)$ in Eq. (22) as

$$\text{CSC}^-(\text{MON}) = \text{Corr}\left[\frac{(S_T/S_t - K/S_t)^+}{E[(S_T/S_t - K/S_t)^+]} - \frac{1_{(K/S_t,\infty)}(S_T/S_t)}{E[1_{(K/S_t,\infty)}(S_T/S_t)]}, \text{CDS}_T^{6m} - \text{CDS}_t^{6m}\right], \tag{31}$$

where MON $= 1 - K/S_t$, and unconditional correlations between weekly CDS spread changes and $g(S_T)$ in Eq. (24) as

$$\text{CSP}^-(\text{MON}) = \text{Corr}\left[\frac{1_{(0,K/S_t)}(S_T/S_t)}{E[1_{(0,K/S_t)}(S_T/S_t)]} - \frac{(K/S_t - S_T/S_t)^+}{E[(K/S_t - S_T/S_t)^+]}, \text{CDS}_T^{6m} - \text{CDS}_t^{6m}\right], \tag{32}$$

where MON $= K/S_t - 1$. Fig. 4 shows for various values of MON, CSP^-(MON) and CSC^-(MON) are negative for most of the issuers, and they are highly and positively correlated for various pairs of MONs. These results provide supporting evidence for the condition of Proposition 3 (iii).

Figure 4 here

[11]Proposition 2 requires rankings of issuers based on covariances between payoffs and CDS spreads conditional on the level of CDS spreads. Because the variance of CDS spreads is strongly and positively associated with the level of CDS spreads, the correlations calculated here are already controlled for the level of CDS spreads.

3.4. *Summary statistics*

We denote the value of HSI at the end of a day as S and express the price of warrants $\hat{W}$ and options O as the actual bid-ask average price multiplied by 100 and divided by S. The reason for normalizing by S is so that we can make the price data comparable across time. Defined in this way, the prices of warrants and options are expressed in terms of the percentage of the HSI level. The time to expiration is measured by the number of calendar days and denoted by TTE, and LTE is the log of TTE. The log-price difference of a matched pair of warrant and option, $\hat{d} = \log(\hat{W}) - \log(O)$, is the main variable of interest in this paper, for which normalization by S is inconsequential.[12] LIQ is the proportion of warrant trading attributed to liquidity providers, calculated as the share volume traded by liquidity providers divided by the total share volume for a warrant contract on a day on which the total trading volume is positive. The higher the value of LIQ, the more actively liquidity providers supply liquidity to the market. WVL and OVL are the daily dollar trading volumes normalized by $1000S$ for a warrant and an option, respectively, and DVL is the difference between WVL and OVL. WSP and OSP are the proportional bid-ask spreads for a warrant and an option, respectively, and DSP is their difference. WCS is the warrant contract size, i.e., the number of shares of the underlying assets for one round lot of warrants, and DCS is the difference in contract sizes between derivative warrants and options. VIX is the volatility index of HSI. CDS^{fit} is the annualized CDS spread of a warrant issuer for the remaining tenor of the warrant, fitted (linearly interpolated or extrapolated) from CDS spreads of available tenors. $\text{CDS}\tau^{\text{fit}}$ is the unannualized CDS spread, i.e., CDS^{fit} multiplied by TTE in years, the main variable measuring the counterparty credit risk of the warrant issuers. The percentiles of the distributions of the key variables are reported in Table 3.

Table 3 here

[12] We focus on relative (i.e., proportional) differences, rather than absolute differences, to save space. All of the implications for the absolute differences from the propositions are verified and available upon request.

The sample of matched warrants and options are near the money with the moneyness of majority between -14% and 5%. The warrants typically mature six months after issue, although issuers are allowed to issue warrants that do not mature until five years later at most. The actively traded warrants and options mostly mature within six months. The medians of $\hat{W}$ and O are 2.6% and 2.2%, respectively. Prices of warrants are generally higher than those of options. However, there is a large cross-sectional variation in the price differences between warrants and options, and quite a number of warrants are traded at lower prices than are options. The average price difference between warrants and options is attributed to the liquidity premium of warrants over options, as Li and Zhang (2011) argue, and the irrational lottery-buying behavior of retail investors. We focus on explaining the cross-sectional variation in the price difference between warrant and option pairs rather than their average price difference. The median of LIQ is 0.99, suggesting that liquidity providers supply liquidity actively in general. Other liquidity variables indicate that warrants tend to be more liquid than options.[13] Warrants tend to have smaller proportional bid-ask spreads than options. One contract of warrants corresponds to about one contract of HSI on average, which makes warrants easy to trade by individual investors with limited capital, whereas one contract of options always corresponds to 50 contracts of HSI. The 5th and 95th percentiles of the VIX of HSI are 14% and 42%, respectively. The annualized, fitted CDS spread, CDS^{fit}, has a median of about 0.29%, and the 5th and 95th percentiles are 0.016% and 1.7%, respectively. The unannualized CDS spread, $\text{CDS}\tau^{\text{fit}}$ has a median of 0.046%, and the 5th and 95th percentiles are 0.0017% and 0.42%, respectively. Both CDS^{fit} and $\text{CDS}\tau^{\text{fit}}$ are positively skewed. Panel A2 of Table 3 reports the summary statistics for the put sample, which are quantitatively similar to the whole sample. The puts are slightly more out of the money with shorter time to expiration and have lower, $\hat{W}$, O, $\hat{d}$, and LIQ than the whole sample.

Panels B1 and B2 of Table 3 report the correlations among the explanatory variables

[13] The daily trading volume of warrants has a wide distribution. On about half of the warrants/days, the trading volume of warrants is slightly smaller than that of options, but on the other half of the warants/days, the trading volume of warrants is much greater than that of options.

used in the analysis that follows. CDSτ^{fit} is correlated with other explanatory variables, suggesting the importance of controlling for other variables in the empirical analysis and the challenge of identifying the effect of counterparty credit risk in precise quantitative terms. Not surprisingly, CDS$^{\text{fit}}$ and CDSτ^{fit} have the highest correlation among these variables. The correlations for the whole sample and the put sample are essentially the same.

Fig. 5 shows the time-series plot of the 10th, 50th, and 90th percentiles of the log-price differences between derivative warrants and options, $\hat{d}$, for puts and calls separately. As we can see, the median of the log-price difference is always positive. There are small fluctuations over time in all of these percentiles, but there is no obvious trend or cycle similar to that of CDS spreads, except for a brief episode at the beginning of 2008, for the calls. This suggests that the variation in CDS spreads is not the only variable that affects the log-price difference.

Figure 5 here

Fig. 6 shows the scatter plots of the log-price difference between derivative warrants and options, $\hat{d}$, against CDSτ^{fit}, where these variables are averaged by month and issuer. The plots are shown separately for puts and calls. For the entire sample period of 2005-2014, for both puts and calls, the negative relation between $\hat{d}$ and CDS spread is clear, and the relation is stronger for puts, especially at large CDS spreads. We divide the sample period into the high CDS spread period of 2008-2012 and the low CDS spread period of 2005-2007 and 2013-2014. The scatter plots for the high CDS spread period are similar to those for the full sample period, but for the low CDS spread period, the negative relation between $\hat{d}$ and CDS spread is much weaker, especially for the call sample. Note that the cross-sectional variation in the CDS spread is much smaller for the low CDS spread period, indicating that it can be difficult to identify the impact of counterparty credit risk during the period. The initial evidence from the scatter plots suggests that counterparty credit risk is important for warrant pricing during the high CDS spread period, especially for the put warrants. A formal empirical analysis of the effect of counterparty credit risk on warrants pricing controlling for other factors will be conducted below.

Figure 6 here

4. Empirical analysis

4.1. Counterparty credit risk and the price difference between warrants and options

In this subsection, we use linear regression analysis to examine the effects of the counterparty credit risk of warrant issuers on the prices of warrants they issue. The panel regression model is specified as

$$\hat{d} = \beta_1 \mathrm{CDS}\tau^{\mathrm{fit}} + \beta_2 \mathrm{LIQ} + \beta_3 \mathrm{MON} + \beta_4 \mathrm{LTE} + \beta_5 1^p \cdot \mathrm{CDS}\tau^{\mathrm{fit}} + \text{time-fixed effects} + \varepsilon, \quad (33)$$

where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair, and $\mathrm{CDS}\tau^{\mathrm{fit}}$ is the unannualized CDS spread, which measures the counterparty credit risk of the warrant issuer. If the counterparty credit risk is priced in warrants (i.e., warrants issued by banks with greater credit risk are traded with larger discounts), the coefficient of $\mathrm{CDS}\tau^{\mathrm{fit}}$ would be negative. LIQ is the proportion of the warrant trading attributed to liquidity providers. Since there are no data on this figure for the options market, we set it to zero so that LIQ measures the liquidity difference between warrants and options.[14] The moneyness, MON, controls for the behavioral biases of warrant investors. Li, Subrahmanyam, and Yang (2018) find that investors prefer financial products with a highly skewed return distribution, i.e., low MON. Another variable with which to control for the behavioral biases is log time to expiration, LTE. [15] Short-term warrants appear to be cheap and are likely to be preferred by warrant investors. The coefficient of LTE is expected to be negative. Proposition 1 (ii) in

[14] We also use the differences in trading volume, bid-ask spread, and contract size between warrants and options to capture their liquidity differences. LIQ dominates other liquidity measures in explaining the price differences between warrants and options. The results with all these liquidity measures are shown in a robustness check in the next section.

[15] We use LTE instead of TTE because LTE has a greater statistical significance than TTE in most regression specifications.

Section 2 suggests that prices of put warrants are more sensitive to CDS spreads than those of call warrants when CDS spreads on warrant issuers and HSI are negatively quadrant-dependent. We empirically test this proposition by including $1^p \cdot \text{CDS}\tau^{\text{fit}}$ in the regression specification, where 1^p indicates a put. The sign on the interaction term is expected to be negative if prices of put warrants are more sensitive to counterparty credit risk than those of call warrants. We use monthly dummy variables to control for the unobserved factors that affect the time-series variation in $\hat{d}$. The t-statistics are clustered by warrant to adjust for the autocorrelation in errors.

Table 4 here

The results for the entire sample period are shown in Panel A of Table 4. $\text{CDS}\tau^{\text{fit}}$ is negatively and significantly related to $\hat{d}$, controlling for LIQ, MON, and LTE. LIQ is positively and significantly related to $\hat{d}$, consistent with the results reported in Li and Zhang (2011) that the liquidity difference between warrants and options explain their price difference to a certain extent. MON and LTE are negatively related to $\hat{d}$, suggesting that warrant investors exhibit behavioral biases. The regression explains a substantial proportion of variation in $\hat{d}$, indicated by R^2 with time-fixed dummies of 38.4% and R^2 without time-fixed dummies of 31.3%. The coefficient of $\text{CDS}\tau^{\text{fit}}$ is about -5.6, indicating that, on average, a one percentage point increase in $\text{CDS}\tau^{\text{fit}}$ of a warrant issuer leads to a 5.6% decrease in the value of the warrant. Translating into annual terms, a one percentage point increase in the annualized CDS spread of a warrant issuer leads to a 1.15% decrease in the value of the warrant because the average maturity of warrants in our sample is 75 days. The effects of the counterparty credit risk of warrant issuers on warrant pricing are economically significant. Our results can be compared with those reported by Arora, Gandhi, and Longstaff (2012) for the CDS market. These authors find that a 645 basis points increase in the credit spread of a CDS dealer translates into only a one basis point decline in the dealer's spread for selling credit protection. They argue that such a small effect from counterparty credit risk is due to credit risk mitigation mechanisms, such as collateral and netting, in the OTC market. In our case, warrant issuers are not required to put up any collateral against the warrants they issue, which enables identifying the strong effects of counterparty credit risk on the pricing of warrants.

The coefficient of $1^p \cdot \text{CDS}\tau^{\text{fit}}$ is negative and highly significant, indicating the stronger impact of the counterparty credit risk of warrant issuers on the prices of put warrants than on those of call warrants. The results support the prediction of Proposition 1 (ii). The coefficient of $\text{CDS}\tau^{\text{fit}}$ becomes -2.2 and insignificant. The results suggest that the explanatory power of $\text{CDS}\tau^{\text{fit}}$ on $\hat{d}$ comes mostly from put warrants. All of LIQ, MON, and LTE still have the expected signs and are statistically significant when the term $1^p \cdot \text{CDS}\tau^{\text{fit}}$ is included in the model.[16]

Panel B of Table 4 reports the results for the subperiod of 2008-2012 when the CDS spreads are high with large cross-sectional variation. The empirical results on the impact of counterparty credit risk on warrant pricing seem to be slightly stronger for the entire period than for the high CDS spread period because the difference between high and low CDS spread periods helps to identify the impact of counterparty credit risk. We note that the effect of counterparty credit risk on warrant pricing can be identified during the high CDS spread period but not during the low CDS spread period because of the low cross-sectional and time-series variations in CDS spreads in the low CDS spread period. The significance levels of LIQ and MON are slightly reduced, and the significance level of LTE is slightly increased. The coefficient of $1^p \cdot \text{CDS}\tau^{\text{fit}}$ remains negative and highly significant.

Proposition 2 suggests that the difference between put warrants and call warrants is even greater for issuers whose CDS spread is more negatively quadrant-dependent with the HSI. For each issuer, we use the average correlation between payoffs and the CDS spread changes, as Eq. (29) and Eq. (30), across MON as the measure of the quadrant dependence. We divide the 21 warrant issuers into two groups. The 11 issuers with more negative average

[16]Under very mild conditions as stated in Section 2, the coefficient of $\text{CDS}\tau^{\text{fit}}$ should be less than one for the call sample. The estimate appears to be greater than what the theory predicts; however, it is not statistically significant. We do not regard this as evidence against the theory.

correlations are grouped into the More-neg-corr group, while the remaining ten issuers form the Less-neg-corr group. The results in Table 5 show that the magnitude of the coefficient and statistical significance of $1^p \cdot \text{CDS}\tau^{\text{fit}}$ are both greater for the sample of More-neg-corr issuers than for the sample of Less-neg-corr issuers. The results for the high CDS spread sample shown in Panel B are basically the same as those for the entire period.

Table 5 here

4.2. The effects of counterparty credit risk across moneyness

Proposition 3 (iii) suggests that the prices of out-of-the-money put (in-the-money call) warrants are more sensitive to CDS spreads that those of in-the-money put (out-of-the-money call) warrants when the CDS spreads on warrant issuers and the HSI are negatively quadrant-dependent. To test this proposition, we focus on put warrants since the effect of counterparty credit risk on put warrants is stronger, and this more delicate moneyness effect is easier to identify empirically. We run the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 \text{MON} \cdot \text{CDS}\tau^{\text{fit}} + \text{time-fixed effects} + \varepsilon, \quad (34)$$

The sign on the interaction term, $\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$, is expected to be positive if prices of out-of-the-money put warrants are more sensitive to counterparty credit risk than those of their in-the-money counterparts.

Table 6 here

The results are reported in Table 6. For the regression without the interaction term, $\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$, the coefficient of $\text{CDS}\tau^{\text{fit}}$ is negative and significant for the put sample. The interaction term, $\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$, is positive and significant, indicating that out-of-the-money put warrants are more sensitive to counterparty credit risk than in-the-money put warrants. The additional term $\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$ improves the explanatory power of the model, although not by a lot. LIQ, MON, and LTE have the expected signs and are highly significant, same as for the call and put sample. The results regarding the moneyness effect for the high CDS spread period shown in Panel B are essentially the same as those for the entire period.

5. Robustness checks

In general, the partial derivative of $\hat{d}$ with respect to $\mathrm{CDS}\tau^{\mathrm{fit}}$ is a function of strike price, time to expiration, and state variables as discussed in Section 2.2. In the first robustness check, we examine how well the linear specification in Eq. (34) approximates the true relation. To this end, we run the following panel regression for the put sample:

$$\begin{aligned} \hat{d} \;=\; & \beta_1 \mathrm{CDS}\tau^{\mathrm{fit}} + \beta_2 \mathrm{LIQ} + \beta_3 \mathrm{MON} + \beta_4 \mathrm{LTE} + \beta_5 \mathrm{CDS}^{\mathrm{fit}} \cdot \mathrm{CDS}\tau^{\mathrm{fit}} \\ & + \beta_6 \mathrm{LIQ} \cdot \mathrm{CDS}\tau^{\mathrm{fit}} + \beta_7 \mathrm{MON} \cdot \mathrm{CDS}\tau^{\mathrm{fit}} + \beta_8 \mathrm{LTE} \cdot \mathrm{CDS}\tau^{\mathrm{fit}} \\ & + \beta_9 \log(\mathrm{VIX}) \cdot \mathrm{CDS}\tau^{\mathrm{fit}} + \text{time-fixed effects} + \varepsilon. \end{aligned} \tag{35}$$

In this specification, we include the interaction terms of $\mathrm{CDS}\tau^{\mathrm{fit}}$ with MON, LTE, and the state variables, including the annualized CDS spread, $\mathrm{CDS}^{\mathrm{fit}}$, and the volatility index of the HSI, VIX. To capture the potential interaction between the liquidity effect and credit risk effect, we include the term $\mathrm{LIQ} \cdot \mathrm{CDS}\tau^{\mathrm{fit}}$ in the model as well.

Table 7 here

The results are reported in Table 7. $\mathrm{MON} \cdot \mathrm{CDS}\tau^{\mathrm{fit}}$ is the most statistically significant interaction term, suggesting the robustness of the moneyness effect. The other interaction terms are not significant, except for $\mathrm{LTE} \cdot \mathrm{CDS}\tau^{\mathrm{fit}}$. The R^2s of the models with all interaction terms are essentially the same as those of the models with the only interaction term of $\mathrm{MON} \cdot \mathrm{CDS}\tau^{\mathrm{fit}}$, which confirms that the linear model Eq. (34) approximates the true model closely and captures the credit risk effect well.

To further address the issue of nonlinearity, we estimate the following semi-parametric regression model,

$$\hat{d} = h(Z) \cdot \text{CDS}\tau^{\text{fit}} + \gamma_1 \text{LIQ} + \gamma_2 \text{MON} + \gamma_3 \text{LTE} + \text{time-fixed effects} + \varepsilon, \tag{36}$$

where $h(\cdot)$ is unspecified, and $Z = (\text{CDS}^{\text{fit}}, \text{LIQ}, \text{MON}, \text{TTE}, \text{VIX})$. By doing so, we relax the restriction that the coefficient of $\text{CDS}\tau^{\text{fit}}$ is a linear function of Z as in Eq. (35). This is a varying-coefficient partially linear model, for which the estimation is standard in the statistics literature, for example, Zhang, Lee, and Song (2002).[17]

The estimated $h(Z)$ as a function of each variable of Z, evaluated at the mean value of other variables of Z, and the 90% confidence bands from 1,000 bootstrap samples are shown in Fig. 7 for the put sample. The figure shows that the estimated $h(Z)$ is significantly negative, as the confidence bands do not cover zero, suggesting the strong impact of counterparty credit risk on warrant pricing. We are also interested in how $h(Z)$ changes with respect to each variable in Z. $h(Z)$ increases monotonically with MON, consistent with the results reported in Table 7, and significantly with narrow confidence bands. There is no significant change in $f(Z)$ as other variables change, except for TTE. All the estimated functions are basically straight lines. The semi-parametric analysis further confirms that the specification of Eq. (34) is a good approximation for the actual relation between log-price differences and CDS spreads.

Figure 7 here

In the second robustness check, we use $\text{CDS}\tau^{\text{6m}}$, which equals the annualized six-month CDS spread multiplied by TTE/365, to measure the credit risk associated with warrant issuers instead of the fitted CDS spreads in the main analysis. For brevity, we term it as the unannualized six-month CDS spread with the understanding that the value is adjusted for the tenor of the warrant. Among available CDSs, the six-month CDS spreads have a tenor matched with those of warrants the best, as warrants have an average time to expiration

[17] Specifically, we use the second-order Gaussian kernel and local linear fitting for the nonparametric estimation. We choose the optimal bandwidth by the cross-validation approach.

of around three months, and most of them are less than a year. The magnitude of the coefficient of $\mathrm{CDS}\tau^{6m}$ is slightly smaller than that reported in the main analysis because the term structure of CDS spreads slopes upward most of the time so that six-month CDS spreads tend to be greater than the fitted CDS spreads. The results suggest that a one percentage point increase in the annualized six-month CDS spread of a warrant issuer leads to a 1% to 1.1% decrease in the value of the warrant, which is again economically meaningful.

Table 8 here

In the last robustness check, we control for other liquidity variables in addition to LIQ. These variables measure liquidity differences between warrant and option pairs, including the difference in daily dollar trading volumes, DVL, the difference in proportional bid-ask spreads, DSP, and the difference in the contract sizes, DCS. The contract size of options is large and fixed at 50, while the contract size of warrants is much smaller but with variation. As a result, the variation in DCS is the same as that of the warrants' contract size. The DCS effect is entirely caused by the variation in the warrants' contract size. The signs on the coefficients of these additional variables are as expected, i.e., a higher liquidity difference is associated with a higher log-price difference. However, many of them are not statistically significant. More importantly, adding new liquidity variables does not change the main results. Overall, these additional tests suggest a robust finding of the negative effects of counterparty credit risk on the prices of warrants, especially for put warrants.

Table 9 here

6. Conclusion

In this paper, we examine whether counterparty credit risk is priced in vulnerable derivatives—a question that has attracted much theoretical development but few successful empirical studies. We conduct our analysis using derivative warrants and options data from the Hong Kong market for the period from 2005 to 2014. The use of derivative warrants data in this study provides a fresh perspective on the effect of counterparty credit risk on derivatives pricing. Derivative warrants are option-like structured products issued by financial institutions, and they are subject to the counterparty credit risk of the issuers. Exchange-traded options are not affected by credit risk due to margin requirements. Therefore, the price differences between derivative warrants and options reflect the credit risk of warrant issuers, among others. In addition, derivative warrants are exchange traded and are not subject to the credit mitigation mechanisms, such as collateral and netting, required in the OTC market. Since issuers take short positions in derivative warrant transactions, the counterparty credit risk associated with derivative warrants always comes from the issuers' side, as opposed to forward-type derivatives, for which the counterparty credit risk comes from both sides of the transaction. Employing these features of the data in this study enables identifying the credit risk associated with derivatives easily and allows a straightforward test of the pricing impact of credit risk on derivatives.

We examine the cross-sectional relation between the log-price differences of matched derivative warrant and option pairs written on the HSI, and the counterparty credit risk of warrant issuers, measured by their CDS spreads. We find that CDS spreads are strongly and negatively related to price differences, especially during the global financial crisis of 2008 and the European sovereign debt crisis of 2011-2012. During these periods, the level and cross-sectional variation of CDS spreads of warrant issuers are much greater than those before and after the corresponding crises. The pricing effect of credit risk is economically significant. On average, a one percentage point increase in the CDS spread on an investment bank leads to a 1%-1.1% decrease in the price of the derivative warrant issued by the bank. Our results also indicate that the prices of put derivative warrants are more sensitive to the counterparty credit risk of warrant issuers than those of call derivative warrants. This is implied by our theoretical analyses given that the counterparty credit risk measured by the CDS spreads on warrant issuers are negatively dependent with the HSI. The counterparty credit risk of institutions whose CDS spreads are more negatively dependent with the HSI has a stronger effect on their put derivative warrants. Another implication derived from our theoretical analyses is that the effect of CDS spread on the proportional prices of put derivative warrants becomes stronger for OTM puts. These findings are robust to various specifications of CDS spreads and sample selection.

The contribution of the paper can be summarized as follows. First, we show for the first time in the literature that counterparty credit risk has a strong impact on derivatives pricing. Second, we find evidence that the impact depends on the dependence nature of the credit risk and the underlying of the derivatives, consistent with the theory. Third, we verify a more delicate relation between the credit risk discount in derivative prices and their moneyness. Overall, our results highlight the importance of counterparty credit risk for the pricing of derivative securities.

References

Arora, N., Gandhi, P., Longstaff, F., 2012. Counterparty credit risk and the credit default swap market. Journal of Financial Economics 103, 280-293.

Bates, D., 2000. Post-'87 crash fears in the S&P 500 futures option market. Journal of Econometrics 94, 181-238.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81, 637-659.

Bomfim, A., 2002. Counterparty credit risk in interest rate swaps during times of market stress. Unpublished working paper. Federal Reserve Board.

Broadie, M., Chernov, M., Johannes, M., 2007. Model specification and risk premia: evidence from futures options. Journal of Finance 62, 1453-1490.

Chan, Y., Wei, K., 2001. Price and volume effects associated with derivative warrant issuance on the Stock Exchange of Hong Kong. Journal of Banking and Finance 25, 1401-1426.

Chen, K., Wu., L, 2001. Introduction and expiration effects of derivative equity warrants in Hong Kong. International Review of Financial Analysis 10, 37-52.

Chow, Y., Li, J., Liu, M., 2009. Making the derivative warrants market. Unpublished working paper. Chinese University of Hong Kong.

Christoffersen, P., Jacobs, K., Mimouni, K., 2010. Volatility dynamics for the S&P 500: evidence from realized volatility, daily returns, and option prices. Review of Financial Studies 23, 3141-3189.

Chun, A., Namvar, E., Ye, X., Yu, F., 2017. Modeling municipal yields with (and without) bond insurance. Management Science, forthcoming.

Cooper, I., Mello, A., 1991. The default risk on swaps. Journal of Finance 46, 597-620.

Cossin, D., Pirotte, H., 1997. Swap credit risk: an empirical investigation on transaction data. Journal of Banking and Finance 21, 1351-1373.

Cserna, B., Levy, A., Wiener, Z., 2013. Counterparty risk in exchange traded notes (ETNs). Journal of Fixed Income 23, 76-101.

Draper, P., Mak, B., Tang, G., 2001. The derivative warrant market in Hong Kong: relationships with underlying assets. Journal of Derivatives 8, 72-84.

Duan, J., Yan, Y., 1999. Semi-parametric pricing of derivative warrants. Unpublished working paper. Hong Kong University of Science and Technology.

Duffie, D., Huang, M., 1996. Swap rates and credit quality. Journal of Finance 51, 921-949.

Duffie, D., Singleton, K., 1997. An econometric model of the term structure of interest rate swap yields. Journal of Finance 52, 1287-1321.

Eom, Y., Subrahmanyam, M., Uno, J., 2000. Credit risk and the Yen interest rate swap market. Unpublished working paper. Yonsei University, New York University, and Nikkei QUICK Information Technologies.

Eom, Y., Subrahmanyam, M., Uno, J., 2002. Transmission of swap spreads and volatilities in the Japanese swap market. Journal of Fixed Income 12, 6-28.

Eraker, B., 2004. Do stock prices and volatility jump? Reconciling evidence from spot and option prices. Journal of Finance 59, 1367-1403.

Fung, J., Zeng, T., 2012. Are derivative warrants overpriced? Journal of Futures Markets 32, 1144-1170.

Hull, J., White, A., 1995. The impact of default risk on the prices of options and other derivatives securities. Journal of Banking and Finance 19, 299-322.

Jarrow, R., Turnbull, S., 1995. Pricing derivatives on financial securities subject to credit risk. Journal of Finance 50, 53-85.

Jarrow, R., Yu, F., 2001. Counterparty risk and the pricing of defaultable securities. Journal of Finance 56, 1765-1799.

Johnson, H., Stulz, R., 1987. The pricing of options with default risk. Journal of Finance 42, 267-280.

Jones, C. S., 2003. The dynamics of stochastic volatility: evidence from underlying and option markets. Journal of Econometrics 116, 181-224.

Klein, P., 1996. Pricing Black-Scholes options with correlated credit risk. Journal of Banking and Finance 20, 1121-1129.

Li, G., Zhang, C., 2011. Why are derivative warrants more expensive than options? An empirical study. Journal of Financial and Quantitative Analysis 46, 275-297.

Li, G., Zhang, C., 2013. Diagnosing affine models of options pricing: evidence from VIX. Journal of Financial Economics 107, 199-219.

Li, X., Subrahmanyam, A., Yang, X., 2018. Can financial innovation succeed by catering to behavioral preferences? Evidence from a callable options market. Journal of Financial Economics 128, 38-65.

Litzenberger, R., 1992. Swaps: plain and fanciful. Journal of Finance 47, 831-850.

Liu, J., Longstaff, F., Mandell, R., 2006. The market price of risk in interest rate swaps: the roles of default and liquidity risks. Journal of Business 79, 2337-2359.

Minton, B., 1997. An empirical examination of basic valuation models for plain vanilla US interest rate swaps. Journal of Financial Economics 44, 251-277.

Pan, J., 2002. The jump-risk premia implicit in options: evidence from an integrated time-series study. Journal of Financial Economics 63, 3-50.

Sorensen, E., Bollier, T., 1994. Pricing swap default risk. Financial Analysts Journal 50, 23-33.

Sun, T., Sundaresan, S., Wang, C., 1993. Interest rate swaps: an empirical investigation. Journal of Financial Economics 36, 77-99.

Yu, F., 2007. Correlated defaults in intensity-based models. Mathematical Finance 17, 155-173.

Zhang, W., Lee, S., Song, X., 2002. Local polynomial fitting in semivarying coefficient model. Journal of Multivariate Analysis 82, 116-188.

Table 1
Numbers of derivative warrants by issuer
This table reports the names of derivative warrant issuers and the numbers of derivative warrants written on the Hang Seng Index issued by each one. The second to fifth columns are, respectively, the numbers of calls, puts, all derivative warrants, and the proportion of derivative warrants in the entire sample, from each issuer. The last column is the number of daily observations. The sample period is from January 2005 to December 2014.

Issuer	Call	Put	Total	Prop (%)	Obs
ABN AMRO	17	20	37	1.15	637
Barclays	42	34	76	2.37	1,074
Bank of China	30	29	59	1.84	1,563
BNP Paribas	120	137	257	8.00	6,065
Credit Suisse	81	76	157	4.89	3,763
Citigroup	16	17	33	1.03	993
Deutsche Bank	146	179	325	10.12	6,536
Daiwa	33	36	69	2.15	1,745
Goldman Sachs	103	132	235	7.31	5,254
HSBC	93	92	185	5.76	5,442
JP Morgan	74	60	134	4.17	3,949
KBC	175	202	377	11.73	10,089
Macquarie Bank	112	114	226	7.03	6,815
Merrill Lynch	58	69	127	3.95	3,271
Morgan Stanley	3	12	15	0.47	342
Nomura	18	12	30	0.93	567
Rabobank	27	30	57	1.77	1,297
Royal Bank of Scotland	27	26	53	1.65	1,240
Standard Chartered Bank	31	37	68	2.12	1,860
Societe Generale	254	265	519	16.15	13,059
UBS	96	78	174	5.42	3,232
All	1,556	1,657	3,213	100.00	78,793

Table 2
CDS spreads on issuers
This table reports the mean and the standard deviation (std) of daily six-month CDS spreads in percentage points of each derivative warrant issuer. Results are reported for the entire sample period of January 2005 to December 2014, and for two subperiods, where one is the high CDS spread period of January 2008 to December 2012, and the other is the low CDS spread period of January 2005 to December 2007 and January 2013 to December 2014.

	05–14		08–12		05–07 & 13-14	
Issuer	mean	std	mean	std	mean	std
ABN AMRO	0.560	0.628	0.988	0.628	0.128	0.156
Barclays	0.496	0.574	0.879	0.590	0.109	0.114
Bank of China	0.517	0.599	0.825	0.707	0.206	0.156
BNP Paribas	0.393	0.511	0.696	0.571	0.087	0.097
Credit Suisse	0.392	0.468	0.685	0.510	0.097	0.076
Citigroup	0.892	1.486	1.673	1.780	0.104	0.082
Deutsche Bank	0.397	0.437	0.683	0.457	0.109	0.091
Daiwa	0.537	0.674	0.909	0.776	0.163	0.161
Goldman Sachs	0.910	1.168	1.635	1.278	0.179	0.172
HSBC	0.300	0.344	0.511	0.372	0.087	0.086
JP Morgan	0.326	0.378	0.552	0.420	0.098	0.071
KBC	0.852	1.072	1.593	1.083	0.104	0.098
Macquarie Bank	0.900	1.423	1.661	1.693	0.134	0.101
Merrill Lynch	1.158	1.560	2.129	1.694	0.178	0.291
Morgan Stanley	1.398	2.265	2.587	2.706	0.199	0.235
Nomura	0.598	0.781	1.020	0.910	0.172	0.175
Rabobank	0.288	0.355	0.492	0.397	0.082	0.097
Royal Bank of Scotland	0.679	0.751	1.228	0.705	0.126	0.151
Standard Chartered Bank	0.447	0.632	0.762	0.763	0.131	0.120
Societe Generale	0.570	0.737	1.025	0.808	0.112	0.127
UBS	0.476	0.643	0.874	0.708	0.074	0.072
Average	0.623	0.833	1.115	0.931	0.128	0.130

Table 3
Summary statistics
Panels A1 and A2 of the table report the 5th, 25th, 50th, 75th, and 95th percentiles of the distributions of

MON:	moneyness;
TTE:	time to expiration in days;
LTE:	log(TTE);
$\hat{W}$ (O):	closing bid-ask average of derivative warrant (option) prices, normalized by the Hang Seng Index level and multiplied by 100;
$\hat{d}$:	log-price difference between derivative warrants and options, $\log(\hat{W}) - \log(O)$;
LIQ:	proportion the trading of derivative warrants attributed to liquidity providers;
WVL:	daily dollar trading volume of derivative warrants, normalized by the Hang Seng Index level and 1,000;
OVL:	daily dollar trading volume of options, normalized by the Hang Seng Index level and 1,000;
DVL:	difference in dollar trading volumes, WVL - OVL;
WSP:	proportion bid-ask spread of derivative warrants;
OSP:	proportion bid-ask spread of options;
DSP:	difference in proportion bid-ask spreads, WSP - OSP;
WCS:	contract size of derivative warrants, number of underlying assets for one round lot of derivative warrants;
DCS:	difference in contract sizes between derivative warrants and options;
VIX:	volatility index of the Hang Seng Index;
CDS^{fit}:	annualized, fitted CDS spread in percentage points;
$\text{CDS}\tau^{\text{fit}}$:	unannualized, fitted CDS spread in percentage points, $\text{CDS}^{\text{fit}} \cdot \text{TTE}/365$.

Panel A1 is for the whole sample, and Panel A2 is for the put sample. Panel B1 and B2 report the correlations among MON, LTE, LIQ, log(VIX), CDS^{fit}, and $\text{CDS}\tau^{\text{fit}}$ for the whole sample and put sample, respectively. The sample period is from January 2005 to December 2014.

Table 3 (cont'd)

A1. All

	P5	P25	P50	P75	P95
MON	-0.1445	-0.0645	-0.0274	0.0025	0.0475
TTE	17	43	66	95	165
LTE	2.8332	3.7612	4.1897	4.5539	5.1059
$\hat{W}$	0.5655	1.3953	2.6065	4.3497	7.9816
O	0.4405	1.1214	2.2037	3.8171	7.2871
$\hat{d}$	-0.0132	0.0524	0.1348	0.2444	0.5098
LIQ	0.0000	0.6430	0.9892	1.0000	1.0000
WVL	0.0002	0.0026	0.0175	0.1945	3.9721
OVL	0.0013	0.0073	0.0339	0.1515	0.6908
DVL	-0.5751	-0.0766	-0.0026	0.1129	3.8398
WSP	0.0065	0.0127	0.0263	0.0690	0.2609
OSP	0.0146	0.0273	0.0477	0.0854	0.1793
DSP	-0.1531	-0.0517	-0.0162	0.0213	0.1962
WCS	0.6944	1.0000	1.2500	1.6129	2.5641
DCS	-49.3056	-49.0000	-48.7500	-48.3871	-47.4359
VIX	0.1422	0.1692	0.1959	0.2452	0.4220
$\mathrm{CDS}^{\mathrm{fit}}$	0.0160	0.0714	0.2871	0.6962	1.7034
$\mathrm{CDS}\tau^{\mathrm{fit}}$	0.0017	0.0121	0.0456	0.1235	0.4153

A2. Puts

	P5	P25	P50	P75	P95
MON	-0.1583	-0.0736	-0.0367	-0.0054	0.0396
TTE	17	43	66	92	161
LTE	2.8332	3.7612	4.1897	4.5218	5.0814
$\hat{W}$	0.5243	1.2360	2.4123	4.1546	8.0011
O	0.4182	1.0106	2.0366	3.6214	7.3130
$\hat{d}$	-0.0183	0.0539	0.1336	0.2368	0.4755
LIQ	0.0000	0.4598	0.9811	1.0000	1.0000
WVL	0.0002	0.0025	0.0177	0.1884	3.3159
OVL	0.0012	0.0074	0.0350	0.1553	0.7040
DVL	-0.5807	-0.0796	-0.0030	0.1024	3.1520
WSP	0.0067	0.0132	0.0282	0.0741	0.2667
OSP	0.0145	0.0272	0.0475	0.0837	0.1785
DSP	-0.1459	-0.0487	-0.0145	0.0238	0.2067
WCS	0.6711	1.0000	1.2500	1.5385	2.5000
DCS	-49.3289	-49.0000	-48.7500	-48.4615	-47.5000
VIX	0.1424	0.1686	0.1957	0.2452	0.4200
$\mathrm{CDS}^{\mathrm{fit}}$	0.0139	0.0578	0.2583	0.6597	1.6556
$\mathrm{CDS}\tau^{\mathrm{fit}}$	0.0016	0.0100	0.0400	0.1142	0.3872

Table 3 (cont'd)

B1. Correlations: all

	MON	LTE	LIQ	log(VIX)	CDS^{fit}
LTE	-0.2739				
LIQ	0.1494	0.2839			
log(VIX)	-0.2490	0.0016	-0.1666		
CDS^{fit}	-0.0746	0.0210	0.0241	0.4501	
$CDS\tau^{fit}$	-0.1580	0.3345	0.1141	0.3688	0.8132

B2. Correlations: puts

	MON	LTE	LIQ	log(VIX)	CDS^{fit}
LTE	-0.2414				
LIQ	0.1677	0.3049			
log(VIX)	-0.1616	-0.0494	-0.2248		
CDS^{fit}	-0.0074	-0.0106	0.0428	0.4270	
$CDS\tau^{fit}$	-0.0854	0.3244	0.1391	0.3344	0.8001

Table 4
Counterparty credit risk and the price difference between derivative warrants and options
This table reports coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 1^p \cdot \text{CDS}\tau^{\text{fit}} + \text{time-fixed effects} + \varepsilon,$$

where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $\text{CDS}\tau^{\text{fit}}$ is the unannualized, fitted CDS spread; LIQ is the proportion of the trading of derivative warrants attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; 1^p indicates a put; and time-fixed effects are captured by monthly dummies. T-statistics are clustered by warrant and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panel A is for the entire sample period from January 2005 to December 2014, and Panel B is for the high CDS spread period from January 2008 to December 2012.

A. Entire period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE	$1^p \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
-5.61	0.18	-1.44	-0.01		0.384	0.313
(-4.8)	(35.7)	(-29.6)	(-3.8)			
-2.20	0.18	-1.44	-0.01	-7.61	0.386	0.315
(-1.8)	(35.9)	(-28.8)	(-3.8)	(-3.9)		
B. High CDS spread period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE	$1^p \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
-5.00	0.19	-1.44	-0.02		0.374	0.314
(-4.0)	(26.2)	(-23.3)	(-5.0)			
-1.94	0.19	-1.44	-0.02	-6.90	0.376	0.316
(-1.5)	(26.4)	(-22.7)	(-4.9)	(-3.6)		

Table 5
The effects of the correlation between counterparty credit risk and the underlying value
This table reports coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 1^p \cdot \text{CDS}\tau^{\text{fit}} + \text{time-fixed effects} + \varepsilon,$$

where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $\text{CDS}\tau^{\text{fit}}$ is the unannualized, fitted CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; 1^p indicates a put; and time-fixed effects are captured by monthly dummies. T-statistics are clustered by warrant and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panel A is for the entire sample period from January 2005 to December 2014, and Panel B is for the high CDS spread period from January 2008 to December 2012. More-neg-corr indicates the sample of warrants issued by the 11 banks with more negative average CDS spread-payoffs correlations, and Less-neg-corr indicates the sample of warrants issued by the 10 banks with less negative average CDS spread-payoffs correlations.

	$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE	$1^p \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
A. Entire period							
More-neg-corr	-2.03	0.19	-1.52	-0.01	-10.04	0.413	0.342
	(-1.2)	(27.4)	(-27.5)	(-2.5)	(-4.7)		
Less-neg-corr	-2.24	0.16	-1.30	-0.01	-3.18	0.368	0.263
	(-1.2)	(23.1)	(-15.9)	(-3.1)	(-0.9)		
B. High CDS spread period							
More-neg-corr	-1.63	0.20	-1.50	-0.02	-9.23	0.403	0.339
	(-1.0)	(19.8)	(-21.7)	(-3.4)	(-4.4)		
Less-neg-corr	-2.16	0.17	-1.33	-0.02	-2.56	0.352	0.271
	(-1.1)	(18.8)	(-12.6)	(-3.6)	(-0.7)		

Table 6
The effects of counterparty credit risk across moneyness
This table reports coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 \text{MON} \cdot \text{CDS}\tau^{\text{fit}} + \text{time-fixed effects} + \varepsilon,$$

for the sample of put derivative warrants, where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $\text{CDS}\tau^{\text{fit}}$ is the unannualized, fitted CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; and time-fixed effects are captured by monthly dummies. T-statistics are clustered by warrant and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panel A is for the entire sample period from January 2005 to December 2014, and Panel B is for the high CDS spread period from January 2008 to December 2012.

A. Entire period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE	$\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
-5.46	0.17	-1.24	-0.02		0.386	0.290
(-4.1)	(28.3)	(-24.6)	(-6.2)			
-2.23	0.17	-1.33	-0.02	56.24	0.388	0.291
(-1.6)	(28.4)	(-22.3)	(-6.5)	(3.1)		
B. High CDS spread period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE	$\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
-4.73	0.16	-1.22	-0.03		0.397	0.304
(-3.3)	(21.9)	(-20.4)	(-5.8)			
-1.35	0.17	-1.35	-0.03	57.98	0.399	0.304
(-0.9)	(22.1)	(-17.7)	(-6.2)	(2.9)		

Table 7
Robustness check: nonlinearity
This table reports coefficient estimates of the following panel regression:

$$\begin{aligned}\hat{d} \;=\;& \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 \text{CDS}^{\text{fit}} \cdot \text{CDS}\tau^{\text{fit}} \\ &+ \beta_6 \text{LIQ} \cdot \text{CDS}\tau^{\text{fit}} + \beta_7 \text{MON} \cdot \text{CDS}\tau^{\text{fit}} + \beta_8 \text{LTE} \cdot \text{CDS}\tau^{\text{fit}} \\ &+ \beta_9 \log(\text{VIX}) \cdot \text{CDS}\tau^{\text{fit}} + \text{time-fixed effects} + \varepsilon,\end{aligned}$$

for the sample of put derivative warrants, where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; CDS^{fit} ($\text{CDS}\tau^{\text{fit}}$) is the annualized (unannualized), fitted CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; VIX is the volatility index of the Hang Seng Index; and time-fixed effects are captured by monthly dummies. T-statistics are clustered by warrants and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panel A is for the entire sample period from January 2005 to December 2014, and Panel B is for the high CDS spread period from January 2008 to December 2012.

A. Entire period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE			
-25.90	0.18	-1.33	-0.02			
(-1.6)	(25.2)	(-22.7)	(-5.7)			
$\text{CDS}^{\text{fit}} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{LIQ} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{LTE} \cdot \text{CDS}\tau^{\text{fit}}$	$\log(\text{VIX}) \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
126.66	-5.31	60.40	5.89	3.82	0.389	0.289
(1.7)	(-1.6)	(3.6)	(2.2)	(0.9)		
B. High CDS spread period						
$\text{CDS}\tau^{\text{fit}}$	LIQ	MON	LTE			
-29.52	0.17	-1.35	-0.03			
(-1.8)	(18.8)	(-18.2)	(-5.2)			
$\text{CDS}^{\text{fit}} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{LIQ} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{MON} \cdot \text{CDS}\tau^{\text{fit}}$	$\text{LTE} \cdot \text{CDS}\tau^{\text{fit}}$	$\log(\text{VIX}) \cdot \text{CDS}\tau^{\text{fit}}$	R_1^2	R_2^2
117.61	-2.69	62.60	6.59	4.88	0.401	0.300
(1.5)	(-0.8)	(3.5)	(2.4)	(1.1)		

Table 8
Robustness check: six-month CDS spreads
Panels A1 and A2 report coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{6\text{m}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 1^p \cdot \text{CDS}\tau^{6\text{m}} + \text{time-fixed effects} + \varepsilon,$$

for the call and put sample, where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $\text{CDS}\tau^{6\text{m}}$ is the unannualized six-month CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; 1^p indicates a put; and time-fixed effects are captured by monthly dummies. Panels B1 and B2 report coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{6\text{m}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 \text{MON} \cdot \text{CDS}\tau^{6\text{m}} + \text{time-fixed effects} + \varepsilon,$$

for the sample of put derivative warrants. T-statistics are clustered by warrant and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panels A1 and B1 are for the entire period from January 2005 to December 2014, and Panels A2 and B2 are for the high CDS spread period from January 2008 to December 2012.

A1. Entire period						
$\text{CDS}\tau^{6\text{m}}$	LIQ	MON	LTE	$1^p \cdot \text{CDS}\tau^{6\text{m}}$	R_1^2	R_2^2
-5.53	0.18	-1.44	-0.01		0.384	0.313
(-4.6)	(35.7)	(-29.6)	(-3.9)			
-2.06	0.18	-1.44	-0.01	-7.76	0.386	0.315
(-1.6)	(35.9)	(-28.8)	(-3.8)	(-4.0)		
A2. High CDS spread period						
$\text{CDS}\tau^{6\text{m}}$	LIQ	MON	LTE	$1^p \cdot \text{CDS}\tau^{6\text{m}}$	R_1^2	R_2^2
-4.94	0.19	-1.44	-0.02		0.374	0.314
(-3.9)	(26.2)	(-23.3)	(-5.0)			
-1.83	0.19	-1.44	-0.02	-7.04	0.376	0.316
(-1.4)	(26.4)	(-22.7)	(-4.9)	(-3.7)		
B1. Entire period, put sample						
$\text{CDS}\tau^{6\text{m}}$	LIQ	MON	LTE	$\text{MON} \cdot \text{CDS}\tau^{6\text{m}}$	R_1^2	R_2^2
-2.19	0.17	-1.34	-0.02	57.85	0.388	0.291
(-1.6)	(28.4)	(-22.4)	(-6.5)	(3.2)		
B2. High CDS spread period, put sample						
$\text{CDS}\tau^{6\text{m}}$	LIQ	MON	LTE	$\text{MON} \cdot \text{CDS}\tau^{6\text{m}}$	R_1^2	R_2^2
-1.35	0.17	-1.36	-0.03	60.31	0.400	0.304
(-0.9)	(22.1)	(-17.7)	(-6.2)	(3.0)		

Table 9
Robustness check: controlling for alternative liquidity measures
Panels A1 and A2 report coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 1^p \cdot \text{CDS}\tau^{\text{fit}} + \beta_6 \text{DVL} + \beta_7 \text{DSP} + \beta_8 \text{DCS} + \text{time-fixed effects} + \varepsilon,$$

for the call and put sample, where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $\text{CDS}\tau^{\text{fit}}$ is the unannualized, fitted CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; LTE is the log time to expiration in days; 1^p indicates a put; DVL, DSP, and DCS are differences between a matched derivative warrant and option pair in daily dollar trading volumes (divided by the Hang Seng Index level and 10^6), proportional bid-ask spreads, and contract sizes, respectively; and time-fixed effects are captured by monthly dummies. Panels B1 and B2 report coefficient estimates of the following panel regression:

$$\hat{d} = \beta_1 \text{CDS}\tau^{\text{fit}} + \beta_2 \text{LIQ} + \beta_3 \text{MON} + \beta_4 \text{LTE} + \beta_5 \text{MON} \cdot \text{CDS}\tau^{\text{fit}} + \beta_6 \text{DVL} + \beta_7 \text{DSP} + \beta_8 \text{DCS} + \text{time-fixed effects} + \varepsilon,$$

for the sample of put derivative warrants. T-statistics are clustered by warrant and are reported in parentheses. R_1^2 and R_2^2 are the R^2s of the regression model with and without the time-fixed effects, respectively. Panels A1 and B1 are for the entire period from January 2005 to December 2014, and Panels A2 and B2 are for the high CDS spread period from January 2008 to December 2012.

Table 9 (cont'd)

A1. Entire period									
CDSτ^{fit}	LIQ	MON	LTE	$1^p \cdot$ CDSτ^{fit}	DVL	DSP	DCS	R_1^2	R_2^2
-5.61	0.17	-1.46	-0.02		0.23	-0.10	-0.01	0.387	0.323
(-4.7)	(36.0)	(-29.4)	(-5.9)		(0.7)	(-6.7)	(-1.9)		
-2.14	0.17	-1.46	-0.02	-7.73	0.18	-0.10	-0.01	0.389	0.325
(-1.7)	(36.1)	(-28.6)	(-5.9)	(-3.9)	(0.5)	(-6.7)	(-2.0)		
A2. High CDS spread period									
CDSτ^{fit}	LIQ	MON	LTE	$1^p \cdot$ CDSτ^{fit}	DVL	DSP	DCS	R_1^2	R_2^2
-4.94	0.18	-1.46	-0.02		0.15	-0.10	-0.03	0.377	0.319
(-4.0)	(26.3)	(-22.8)	(-6.3)		(0.3)	(-4.8)	(-1.7)		
-1.80	0.18	-1.46	-0.02	-7.07	0.07	-0.10	-0.03	0.379	0.321
(-1.4)	(26.4)	(-22.2)	(-6.2)	(-3.6)	(0.1)	(-4.8)	(-1.8)		
B1. Entire period, put sample									
CDSτ^{fit}	LIQ	MON	LTE	MON $\cdot$ CDSτ^{fit}	DVL	DSP	DCS	R_1^2	R_2^2
-1.78	0.17	-1.42	-0.03	68.07	0.04	-0.06	-0.04	0.393	0.336
(-1.3)	(29.6)	(-22.5)	(-7.0)	(3.5)	(0.1)	(-4.1)	(-4.6)		
B2. High CDS spread period, put sample									
CDSτ^{fit}	LIQ	MON	LTE	MON $\cdot$ CDSτ^{fit}	DVL	DSP	DCS	R_1^2	R_2^2
-0.82	0.17	-1.45	-0.03	65.97	0.37	-0.03	-0.08	0.406	0.324
(-0.6)	(22.6)	(-17.8)	(-6.6)	(3.1)	(0.6)	(-1.6)	(-4.4)		

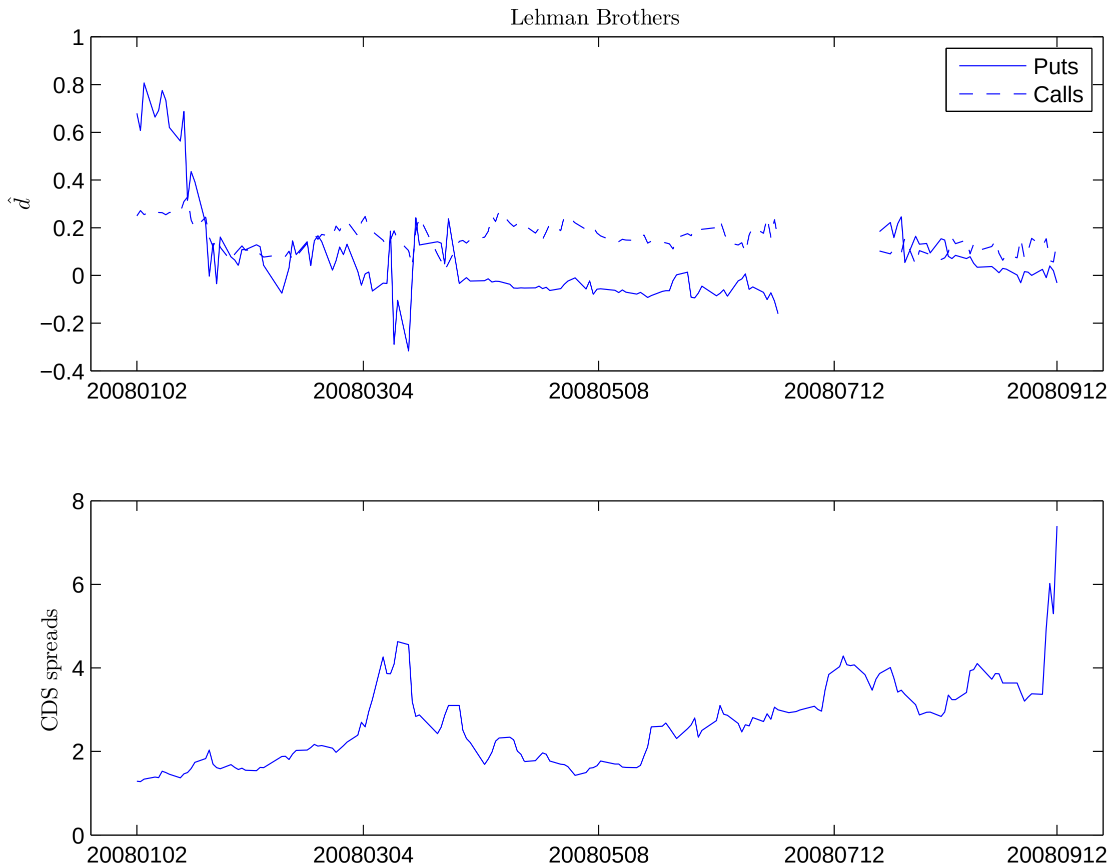

Fig. 1. Derivative warrants issued by Lehman Brothers and its CDS spread

The upper panel shows the daily average log-price difference between derivative warrants issued by Lehman Brothers and the best matched options, $\hat{d}$, for calls and puts separately. The sample includes all warrants when put warrants are available during the period. The first segment of the sample includes warrants on stocks of large companies, and the second segment includes warrants on the Hang Seng Index. There are no put warrants issued by Lehman Brothers between the two segments. The lower panel shows the five-year CDS spread of Lehman Brothers in percentage points. The sample period is from January 2008 to September 2008.

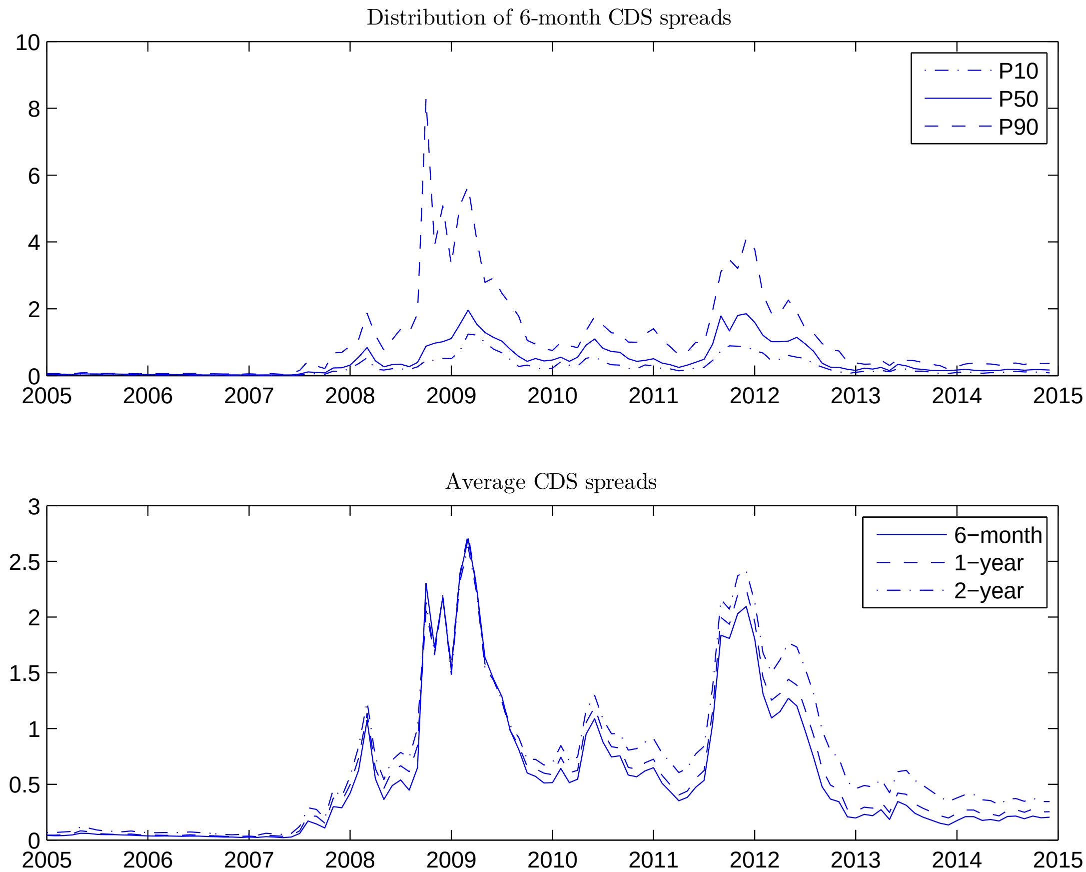

Fig. 2. CDS spreads

Panel A shows the monthly time-series plots of the 10th, 50th, and 90th percentiles of the cross-sectional distribution of the annualized six-month CDS spreads in percentage points of derivative warrant issuers. Panel B shows the monthly time-series plots of the average annualized six-month, one- and two-year CDS spreads in percentage points. The sample period is from January 2005 to December 2014.

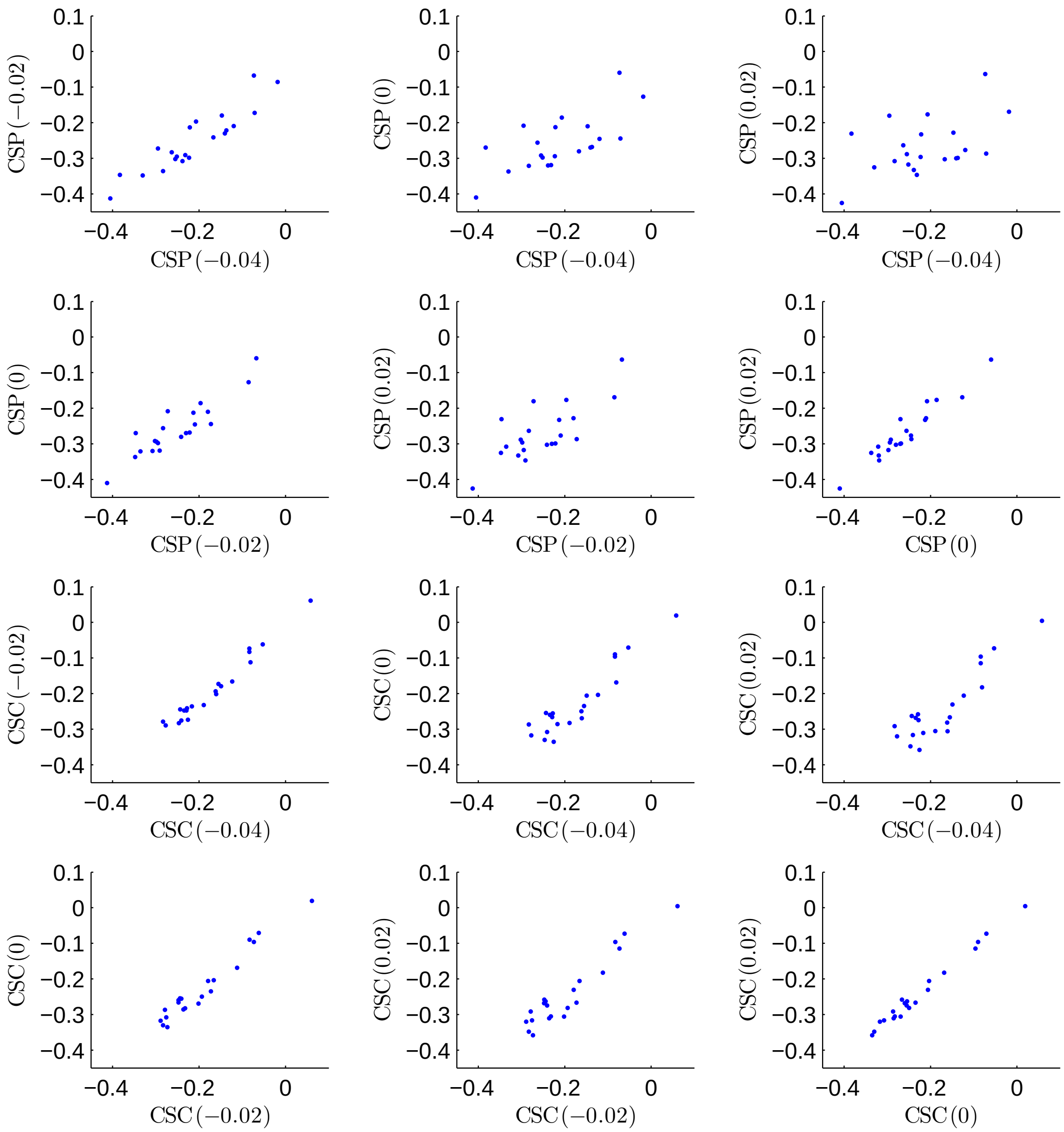

Fig. 3. CSP and CSC

This figure shows the scatter plots among CSP(MON) and CSC(MON) of warrant issuers for various values of moneyness, MON. CSP(MON) is the correlation between negative normalized payoffs of puts with CDS spread changes defined as Eq. (30), and CSC(MON) is the correlation between normalized payoffs of calls with CDS spread changes defined as Eq. (29). The sample period is from January 2005 to December 2014.

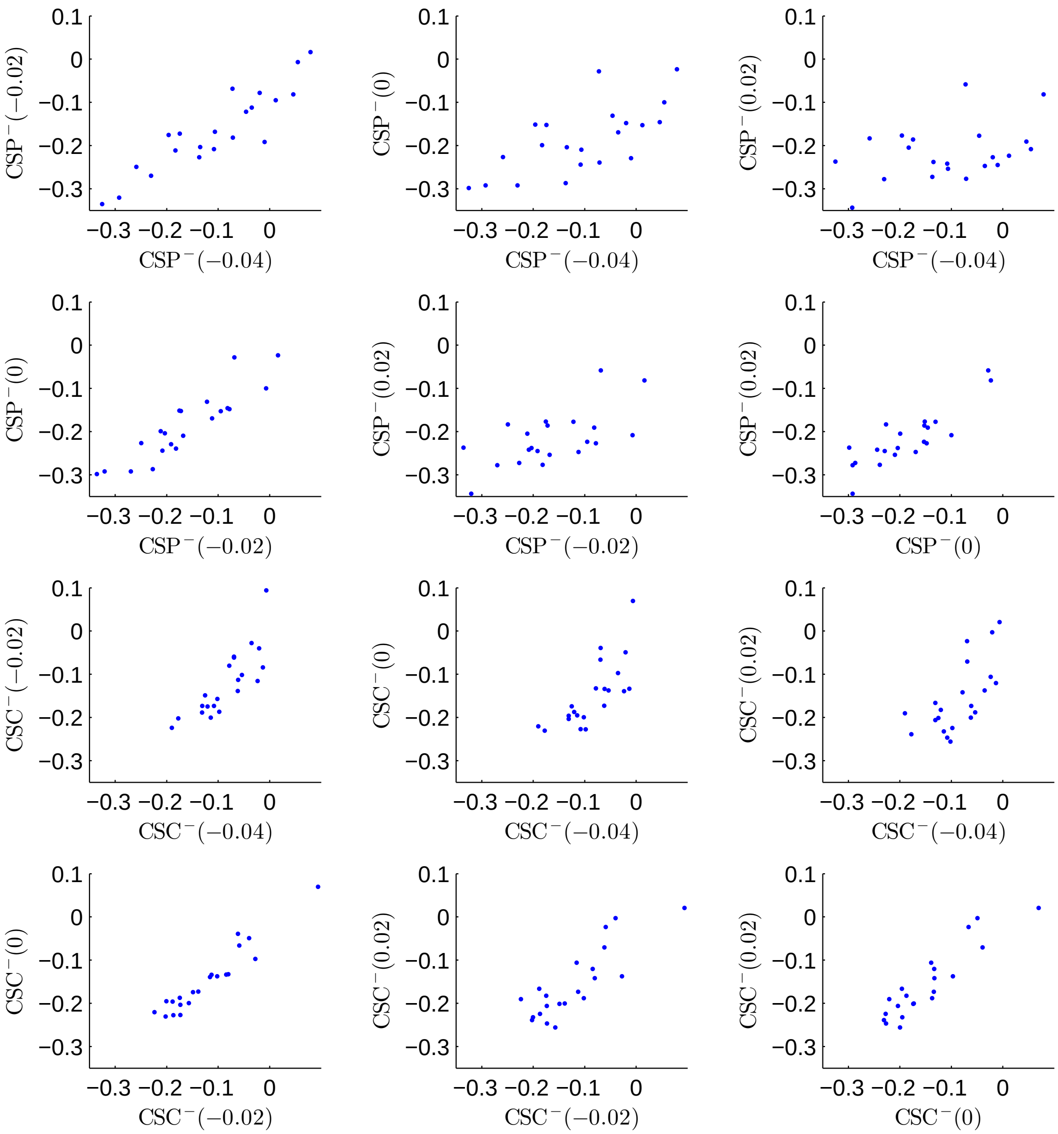

Fig. 4. CSP^- and CSC^-

This figure shows the scatter plots among $CSP^-(MON)$ and $CSC^-(MON)$ of warrant issuers for various values of moneyness, MON. $CSP^-(MON)$ is the correlation between the difference in in-the-money indicators and payoffs of puts with CDS spread changes defined as Eq. (32), and $CSC^-(MON)$ is the correlation between the difference in payoffs and in-the-money indicators of calls with CDS spread changes defined as Eq. (31). The sample period is from January 2005 to December 2014.

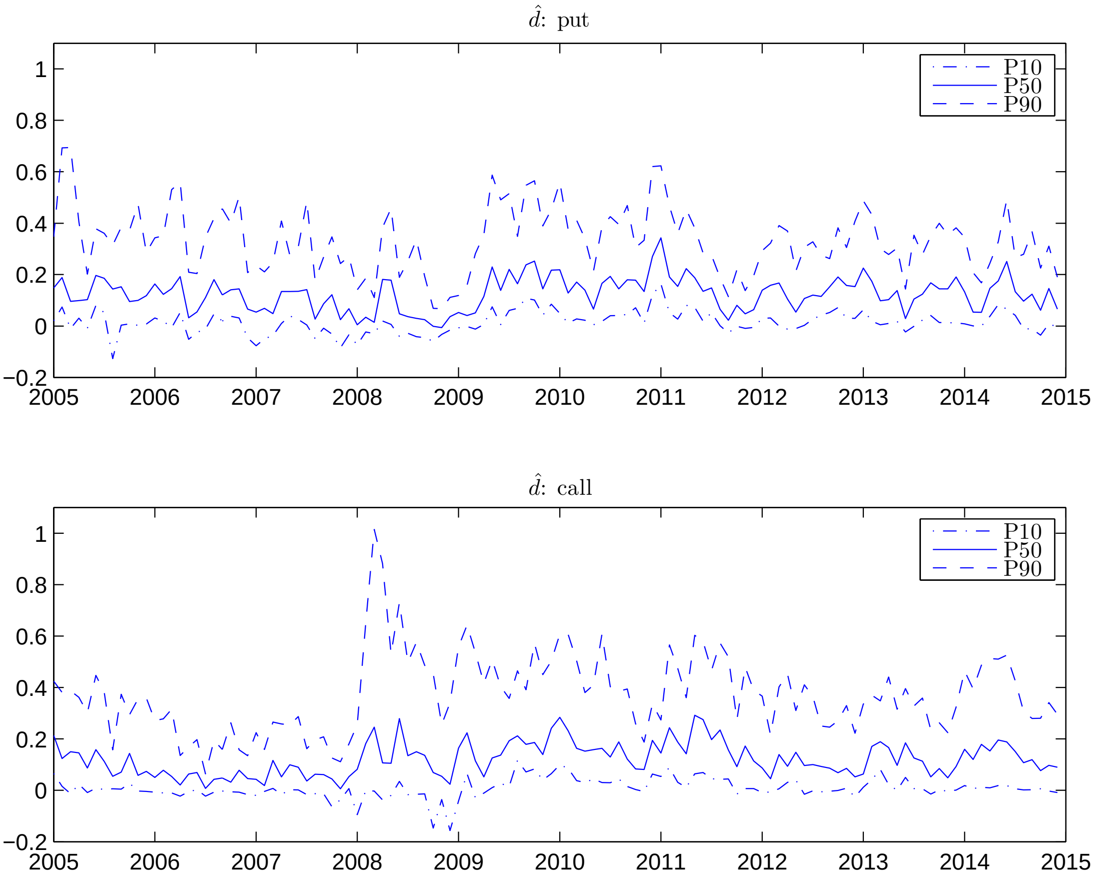

Fig. 5. Log differences in prices between derivative warrants and options

This figures shows the monthly time-series plots of the 10th, 50th, and 90th percentiles of the cross-sectional distribution of the log-price difference between derivative warrants and options, $\hat{d}$. Panel A is for puts, and Panel B is for calls. The sample period is from January 2005 to December 2014.

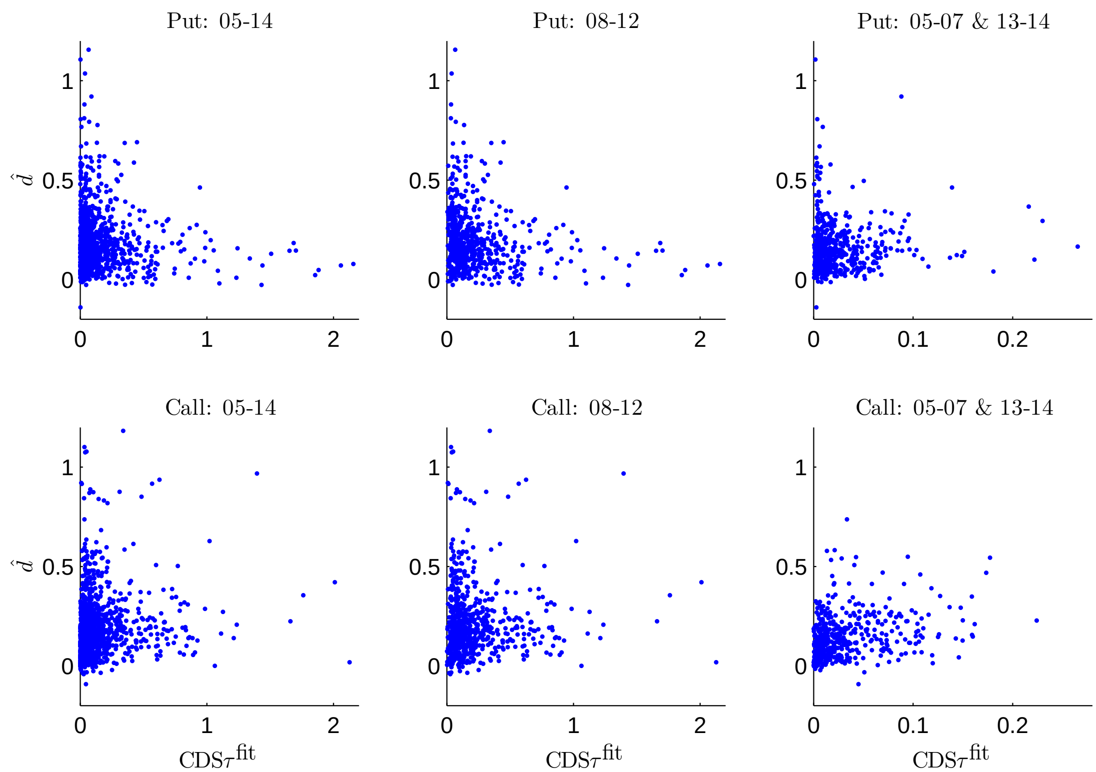

Fig. 6. CDS spreads and log differences in prices between derivative warrants and options

This figure shows the scatter plots of log-price difference between matched derivative warrant and option pairs, $\hat{d}$, against the unannualized, fitted CDS spread in percentage points, $\text{CDS}\tau^{\text{fit}}$. The variables are averaged by month and issuer. The plots are shown separately for puts and calls and for the entire sample period (2005-2014), the high CDS spread period (2008-2012), and the low CDS spread period (consisting of 2005-2007 and 2013-2014).

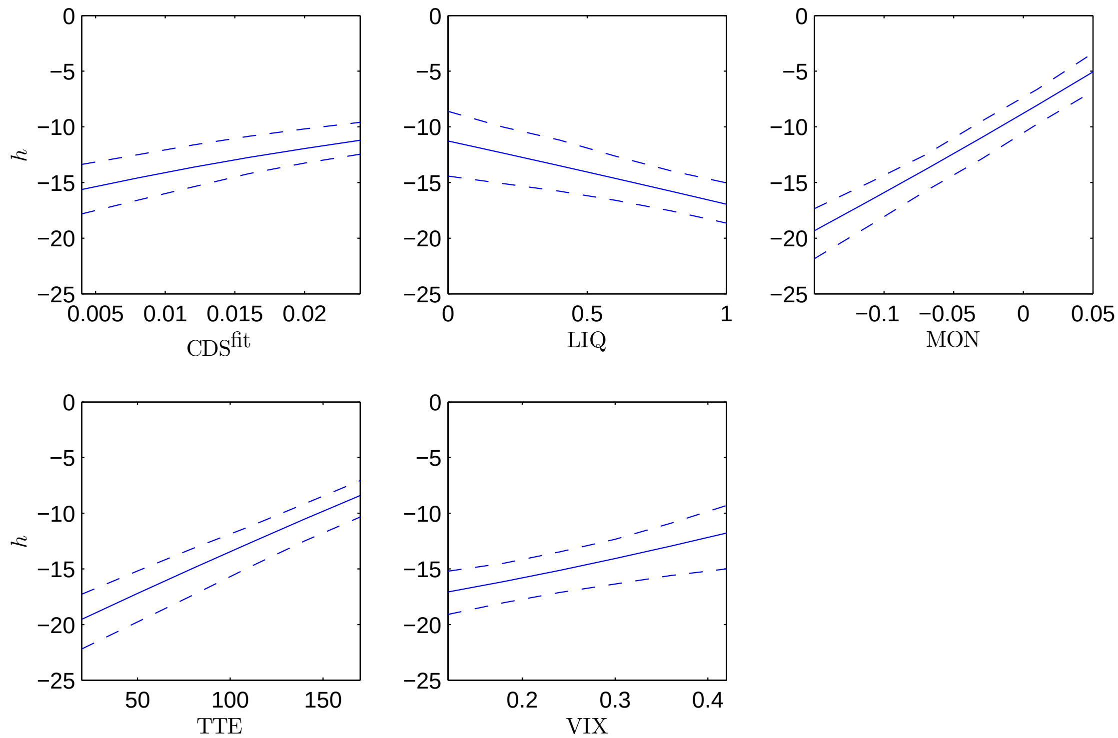

Fig. 7. Semi-parametric estimation of the coefficient of $\text{CDS}\tau^{\text{fit}}$

This figure shows the mean and 90% confidence bands of the coefficient of $\text{CDS}\tau^{\text{fit}}$, $h(Z)$, from the semi-parametric model

$$\hat{d} = h(Z) \cdot \text{CDS}\tau^{\text{fit}} + \gamma_1 \text{LIQ} + \gamma_2 \text{MON} + \gamma_3 \text{LTE} + \text{time-fixed effects} + \varepsilon,$$

for the sample of put derivative warrants, where $\hat{d}$ is the log-price difference between a matched derivative warrant and option pair; $Z = (\text{CDS}^{\text{fit}}, \text{LIQ}, \text{MON}, \text{TTE}, \text{VIX})$; CDS^{fit} ($\text{CDS}\tau^{\text{fit}}$) is the annualized (unannualized), fitted CDS spread; LIQ is the proportion of derivative warrant trading attributed to liquidity providers; MON is the moneyness; TTE is the time to expiration in days; LTE is the log of TTE; VIX is the volatility index of the Hang Seng Index; and time-fixed effects are captured by monthly dummies. $h(Z)$ is plotted as a function of each variable of Z, evaluated at the mean value of other variables of Z. The sample period is from January 2005 to December 2014.