Empirical Test of the Efficiency of UK Covered Warrants Market: Stochastic Dominance and Likelihood Ratio Test Approach

Chia-Ying Chan
Department of Finance
College of Management
Yuan Ze University
Taiwan.

Tel: (+886) 34638800 ext.2670
Fax: (+886) 34354624
sherrychan@saturn.yzu.edu.tw

Christian de Peretti
Laboratory SAF (EA2429), Institute of Financial and Actuarial Sciences
University of Claude Bernard Lyon 1, University of Lyon, France.

Tel: (+33) (0) 619164765
Fax: (+33) (0) 442914829
christian.de-peretti@ec-lyon.fr

Zhuo Qiao*
Faculty of Business Administration
University of Macau
Taipa, Macau, China

Tel: (+853) 8397 4166;
Fax: (+853) 2883 8320
zhuoqiao@umac.mo

Wing-Keung Wong
Department of Economics
Hong Kong Baptist University
Kowloon Tong, Hong Kong

Tel: (+852) 3411-7542
Fax: (+852) 3411-5580
awong@hkbu.edu.hk

* Corresponding author. Address: Department of Finance and Business Economics, Faculty of Business Administration, University of Macau, Avenida Padre Tomás Pereira, Taipa, Macau, China. Tel: +853 8397 4166; fax: +853 2883 8320; e-mail: zhuoqiao@umac.mo

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Abstract

This paper represents the first attempt to apply a stochastic dominance (SD) approach to examine the efficiency of the UK covered warrants market. Our empirical analyses reveal that neither covered warrants nor the underlying shares stochastically dominate the other, indicating the nonexistence of potential arbitrage gains in either wealth or utility, which implies the market efficiency. To complement the SD results, we also employ a likelihood ratio (LR) test to examine information efficiency. A bootstrap methodology is developed to correct the size distortion of the LR test. Our findings show that UK covered warrants returns efficiently reflect the return information of the underlying shares.

Keywords: Covered warrants, Market efficiency, Stochastic dominance, Bootstrap likelihood ratio test

EFM Classification: 350, 440, 760

Introduction

Financial derivatives, developed about four decades ago, have been a topic of interest from market participants and academics. Researchers such as Black (1975), Roll (1977), and Biais and Hillion (1994) claim that the introduction of derivatives conveys information regarding their underlying shares, and that both can share the same information context—to a certain extent, information transmissions exist between options and their underlying assets. In contrast, Stein (1987) argues that the trading of options brings in more noise traders and makes the market less efficient. The results obtained by Figlewski (1981) and Cox (1976) also support this argument.

Unlike options, covered warrants are not standardized: they are traded on stock exchanges or over-the-counter. Many countries now allow investment banks to issue and trade in warrants with different underlying assets—such as shares, indices, commodities, and interest rate futures—without having to comply with sophisticated regulatory requirements.[1] The introduction of covered warrants in the UK was a response to calls for more accessible hedging and speculation tools. As such, there is no margin-requirement for trading covered warrants. Furthermore, covered warrants can be traded directly through the London Stock Exchange (LSE), rather than by applying for a Euronext-Liffe market trading membership. Finally, unlike corporate warrants, covered warrants are not issued by companies on their own shares, and no new shares are issued upon their exercise. The increasing importance of the covered warrants market motivates us to investigate this expanding, but yet academically neglected, market.

Recent studies highlight the difference between option-alike covered warrants and the corresponding trading options (Aitken and Segara, 2005; Petrella, 2006; Abad and Nieto, 2007; Whalley, 2008). Researchers have also indicated that the introduction of covered warrants provides an alternative investment choice for market participants (Abad and Nieto, 2007; Horst and Veld, 2008; Aitken et al., 2010). In addition, covered warrants have gained in popularity amongst retail investors (Aitken and Segara, 2005; Abad and Nieto, 2007; Bartram and Felhe, 2007; Aitken et al., 2010). Previous studies have predominantly focused on price differences between warrants and options. In addition, to our knowledge no previous study has attempted to provide a direct assessment of the relationship between covered warrants market prices and their underlying share prices. The current paper contributes to the existing literature by showing how to directly derive the implied market price from the covered warrants market price, thereby negating the need to consult options trading information or embed any restriction in the pricing model. Another contribution of this paper centers on our investigation of the dominance relationship between traded warrants and their underlying shares. Interestingly, we find that neither warrants nor shares dominate each other, which implies the market is efficient and there is no arbitrage opportunity. We further employ a likelihood ratio (LR) efficiency test to examine the performance of covered warrants returns. Since the original LR efficiency test suffers from a very large size distortion, we have developed a bootstrap version of this test. Our findings support the argument that trading in UK covered warrants is sufficient for hedging and speculation needs. The empirical results in this paper serve as a useful reference for market participants who are interested in trading covered warrants, and hence contribute to the codification of academic research and knowledge regarding this relatively new financial instrument.

In the current study, rather than following the typical approach of testing market efficiency by comparing observed returns with expected returns as generated by equilibrium models such as the capital asset pricing model (CAPM),[2] we first adopt a stochastic dominance approach to examine market efficiency. This approach is superior because it allows us to compare the preferences of different investors and it does not assume any property on asset returns distributions. If an asset or portfolio of assets is preferable to another asset or portfolio, investors always obtain higher expected utilities when holding the dominant asset than when holding the dominated one. Adopting the SD approach to examine the market efficient of West Texas Intermediate crude oil spot and futures contracts, and Lean et al. (2010) confirm there is neither arbitrage nor dominance relationship between the two instruments. Additionally, in this study, to complement the SD methodology, we also provide an alternative method, the GARCH model with a variance equation and the likelihood ratio tests proposed by Xu and Taylor (1995) and Claessen and Mittnik (2002), to test whether the covered warrants returns efficiently reflect the past return information of the underlying shares.

The remainder of this paper is organized as follows: Section 2 briefly describes the literature pertaining to covered warrants and the stochastic dominance rules, as well as the rationale behind the SD tests. The data, sample characteristics, and methodology are discussed in Section 3. The empirical results are provided in Section 4. Section 5 offers conclusions.

2. Background and Literature Review

2.1 UK Covered Warrants Market

The London Stock Exchange (LSE) announced the launch of the covered warrants market on October 28, 2002. Some claim that the introduction of this financial derivative will benefit both individual retail investors and institutional investors, including to get higher gearing ratio, larger range of underlying assets, easier accessibility, better risk management, and lower transaction fees based on the lower stamp duty and trading cost. By November 2003, there were approximately US$419.7 million worth of accumulated call and put warrants. This record was broken in January 2004, when a new high of over 600 covered warrants achieved a trading value of US$813.8 million. By 2006, trading in UK covered warrants reached its peak, as market participants created US$1,346 million in trading value. In view of the increased trading in covered warrants all over the world, there remains scarce academic literature that examines the performance of this derivative, this motivates us to take a deeper look at this financial instrument.

2.2 Literature Review on Covered Warrants

Using data from the Australian covered warrants market between 1997 and 1998, Chan and Pinder (2000) investigate the relative price difference between warrants and options with the same underlying shares. Through a regression analysis, they find that on average the warrants market prices are higher than options market prices; they claim this could due to the liquidity premium in terms of time to maturity and relative trading volume. Abad and Nieto (2007) investigate Spanish warrants data from 2003, and claim that different client types within the warrants and options markets result in the differences in warrants and options prices. Their regression analysis results support the notion that warrants prices are higher than options prices. Horse and Veld (2008) also compare the price differences between 16 Euronext Amsterdam options and warrants; they apply the theoretical warrants pricing model (Black-Scholes and CEV models), and also derive the implied volatility from the actual options to price the covered warrants. They find that investors may perceive warrants as another type of instrument and that the warrants are over-priced over the first five trading days. Peterlla (2006) uses data on 64 Italian covered warrants between 2000 and 2001 to examine the bid-ask spread of covered warrants; the empirical results show that the reservation spread plays an important role in determining the warrant spreads. Furthermore, warrant spreads are linked with the underlying spread.

Bartram and Fehle (2007) apply data from EuRex (options) and EuWax (warrants) in Germany in 2000 to examine the degree of bid-ask spread between warrants and options, and find that with overlapped underlyings, both warrants and options experienced 1-2% lower bid-ask spreads; they claim this is due to competition between options and warrants. Whalley (2008) further derived a theoretical framework to explain the differences between reservations ask and bid prices; they claim the model indicates warrants and other structured products are over-priced. In terms of topics unrelated to bid-ask spread, Aitken and Segara (2005) investigate the introduction effects of the Australian covered warrants market, and confirm a significant negative effect and higher underlying volatility subsequent to the event. Aitken et al. (2010) apply the mean-variance spanning test using data from 1999 to 2003 to examine whether Australian covered warrants can extend the efficient set; their results suggest that the warrants enhance the mean-variance efficient frontier, and that the reason this instrument attracts retail investors is due to its smaller contract size and trading flexibility.

Previous researchers borrow the options price or implied volatility data to examine the value of covered warrants, without directly accessing the dominance relationship or information efficiency between the trading of covered warrants and their underlying shares. This motivates us to provide a more direct method to estimate the share prices "implied" in the actual warrants market prices, and to further investigate the dominated/dominant relationship between investing in warrants and in their underlying shares. Confirmation of the dominance relationship would imply higher expected wealth (utility) can be obtained by trading in the dominant asset. On the other hand, the confirmation of no dominant / dominated relation between covered warrants implied share prices and the actual share market prices may suggest nonexistence of arbitrage opportunity and thereby confirming that the introduction of covered warrants market can improve the trading efficiency.

3. Data and Methodology

3.1 Data

The list of covered warrants was obtained from the LSE and the SG (Société Générale), which is currently the largest covered warrant issuer in the UK. In order to calculate the implied share prices for each corresponding underlying share, information pertaining to the covered warrant price series, maturity, and strike prices was required. At least two covered warrants traded for the same duration and their underlying shares were necessary to calculate the implied prices and volatility. Data series for UK covered warrants and their dividend-adjusted underlying share prices from March 2005 to March 2007 were selected from the Datastream. All UK covered warrants were "European type", such that estimations regarding the equilibrium share prices and implied standard deviations could be made. Further, 71 implied stock price series were derived by inverting the option pricing models (Manaster and Randleman, 1982). The sample set of 71 implied stock prices represented 41 underlying shares listed on the

LSE, which are time series associated with different periods corresponding to different covered warrant contract lives. In addition, daily UK three month LIBOR zero rates were selected from the Datastream as the interest rates for the pricing model. The implied volatility series for the underlying shares were computed to correspond to the everyday covered warrant market prices. Furthermore, as covered warrant expiration dates approach, their prices typically drop dramatically due to decreases in the time value. As such, we excluded the 15 days of trading statistics prior to the expiration.[3] Table 1 presents the details of the sample set and the summery statistics of the implied prices and the underlying share prices.

Table 1. Summary Statistics of the Sample Set

UK list	Type	Listing	Issue price	I V	Mean CW MV	Median CW MV	Mean US MV	Median US MV	UK list	Type	Listing	Issue price	I V	Mean CW MV	Median CW MV	Mean US MV	Median US MV
Ang. Amer	call	2005/4/12	13.3	0.279	1.62	1.50	19836.56	19778.54	M&S	call	2006/7/31	67.75	0.241	63.38	65.63	11212.27	11450.08
	call	2005/4/12	7.8		0.90	0.83	19836.56	19778.54		call	2006/7/31	23.35		24.97	23.49	11212.27	11450.08
	put	2005/4/12	5.35		0.29	0.21	19836.56	19778.54	National grid	call	2006/7/31	6.7	0.259	6.94	6.93	19139.20	19312.69
Ang. Amer	call	2006/7/31	41.2	0.462	20.25	20.63	35890.81	36016.86		call	2006/7/31	2.54		3.08	2.80	19139.20	19312.69
	call	2006/7/31	27.15		10.52	10.83	35890.81	36016.86	Partygaming	call	2006/7/31	33.15	0.569	4.40	0.20	2095.64	1312.40
	put	2006/7/31	20.9		4.63	3.79	35890.81	36016.86		call	2006/7/31	14.85		2.03	0.23	2095.64	1312.40
Ang Amer	put	2006/10/31	21.7	0.413	7.17	7.85	36551.38	36455.90	Pearson	call	2005/4/8	60.65	0.260	7.03	7.08	5316.97	5339.60
	call	2006/10/31	16.3		4.71	4.68	36551.38	36455.90		call	2005/4/8	17		1.35	1.43	5316.97	5339.60
Antofagasta	call	2006/7/31	72.15	0.543	40.04	38.00	4677.51	4642.15		put	2005/4/8	27.6		1.09	1.04	5316.97	5339.60
	call	2006/7/31	53.75		25.52	26.73	4677.51	4642.15	Prudential	call	2005/4/8	7.8	0.262	0.62	0.59	11989.72	11978.31
	put	2006/7/31	52.25		8.78	6.66	4677.51	4642.15		call	2005/4/8	3.13		0.15	0.14	11989.72	11978.31
Arm.hdg	call	2006/7/31	23.35	0.358	12.46	12.06	1623.75	1613.10		put	2005/4/8	1.67		0.13	0.14	11989.72	11978.31
	call	2006/7/31	12.35		5.58	5.51	1623.75	1613.10	Prudential	call	2006/2/24	6.5	0.322	2.26	1.65	14658.18	14358.30
AstraZeneca	call	2005/12/1	28.28	0.338	13.30	14.10	43129.62	42874.82		call	2006/2/24	2.86		0.83	0.37	14658.18	14358.30
	call	2005/12/1	13.42		4.76	5.33	43129.62	42874.82	Prudential	call	2006/7/31	7.2	0.331	6.44	6.20	16034.74	16077.51
	put	2005/12/1	11.17		2.48	2.45	43155.55	42906.55		call	2006/7/31	3.26		2.87	2.80	16034.74	16077.51
AstraZeneca	call	2006/2/24	25.63	0.292	25.34	23.68	47802.83	47244.91	Rbos	call	2006/7/31	15.65	0.269	13.60	11.90	60919.22	59834.90
	call	2006/2/24	10.36		11.10	10.43	47802.83	47244.91		call	2006/7/31	5.6		5.06	4.30	60846.80	59798.54
	put	2006/2/24	19.37		2.63	2.70	47759.62	47218.72		put	2006/7/31	9.2		1.15	0.77	60919.22	59834.90
AstraZeneca	call	2006/7/31	16.4	0.301	12.10	8.60	47382.79	46076.28	Reuters	call	2005/4/8	46.93	0.343	2.10	2.35	5586.74	5592.62
	call	2006/7/31	38.7		4.28	1.10	47382.79	46076.28		call	2005/4/8	23.83		0.77	0.77	5586.74	5592.62
	put	2006/7/31	19.2		8.43	7.43	47382.79	46076.28		put	2005/4/8	27.73		3.05	3.01	5586.74	5592.62
Aviva	call	2005/4/11	6.7	0.258	0.38	0.40	14696.41	14686.59	Reuters	call	2006/2/24	8.14	0.312	1.12	0.43	5138.57	5151.09
	call	2005/4/11	1.83		0.05	0.05	14696.41	14686.59		call	2006/2/24	3.77		0.36	0.14	5136.15	5148.43
	put	2005/4/11	2.38		0.20	0.21	14696.41	14686.59		put	2006/2/24	70.36		35.33	35.70	5138.57	5151.09
B sky	call	2005/4/11	5.7	0.274	0.24	0.21	10175.41	10131.58	Reuters	call	2006/7/31	56.15	0.336	44.64	45.65	5620.64	5655.09
	call	2005/4/11	1.48		0.04	0.03	10175.41	10131.58		call	2006/7/31	30.15		24.82	24.93	5620.64	5655.09
	put	2005/4/11	2.75		0.27	0.31	10175.41	10131.58		put	2006/7/31	22.65		2.72	1.30	5620.64	5655.09
BA	call	2006/7/31	70.25	0.401	72.83	72.75	5511.78	5535.43	Rio Tinto	call	2006/7/31	41.05	0.428	11.29	10.58	27827.89	27856.52
	call	2006/7/31	26.95		33.84	31.43	5511.78	5535.43		call	2006/7/31	21.45		3.72	2.71	27827.89	27856.52
	put	2006/7/31	32		3.90	1.55	5511.78	5535.43		put	2006/7/31	29.95		10.65	10.13	27811.34	27841.13
Bae	call	2005/4/11	28.9	0.266	4.56	3.84	9286.67	9101.45	Rio Tinto	call	2005/12/1	22.5	0.376	21.98	21.96	28785.81	28781.44
	call	2005/4/11	7.3		1.27	0.83	9286.67	9101.45		call	2005/12/1	10.82		10.68	9.53	28928.77	28842.97
	put	2005/4/11	10.05		0.42	0.25	9286.67	9101.45		put	2005/12/1	14.35		1.66	0.57	28928.77	28842.97
Barclays	put	2005/4/11	2.9	0.233	0.22	0.22	35702.12	35883.90	Rio Tinto	call	2006/2/2	28.93	0.396	10.39	10.18	29927.54	29467.18
	call	2005/4/11	3.82		0.22	0.21	35702.12	35883.90		call	2006/2/2	15.77		4.89	4.56	29927.54	29467.18
	call	2005/4/11	1.73		0.07	0.05	35702.12	35883.90		put	2006/2/2	30.75		10.06	9.14	29927.54	29467.18
Barclays	call	2005/12/1	37.34	0.314	18.13	17.04	40416.43	39868.78	Rolls Royce	call	2006/7/31	67.45	0.297	35.31	34.90	8170.42	8109.83
	call	2005/12/1	19.78		6.42	7.10	40398.42	39852.55		call	2006/7/31	30.25		12.35	12.60	8170.42	8109.83
	put	2005/12/1	44.82		12.04	13.50	40492.71	40072.65	Saga group	call	2006/10/3	23.15	0.372	10.93	11.03	3357.38	3398.00
Barclays	call	2006/2/24	58.61	0.289	16.34	10.10	41740.92	42156.73		call	2006/10/3	12.65		4.30	4.70	3357.38	3398.00
	call	2006/2/24	22.77		4.76	1.14	41740.92	42156.73		put	2006/10/3	23.35		5.86	4.45	3357.38	3398.00
	put	2006/2/24	53.31		21.51	21.01	41751.40	42156.73	Shire	call	2006/7/31	15.45	0.334	13.40	14.50	5044.31	5172.04
Barclays	call	2006/7/31	93.45	0.302	77.49	77.44	46235.74	46208.53		call	2006/7/31	7.55		7.36	8.00	5044.31	5172.04
	call	2006/7/31	40.85		36.44	35.75	46235.74	46208.53	Smith	call	2006/7/31	9.98	0.308	7.05	5.98	5447.62	5331.85
	put	2006/7/31	26.15		2.59	1.18	46235.74	46208.53		call	2006/7/31	4.26		2.62	2.24	5447.62	5331.85
Batob	call	2005/4/11	9.35	0.226	1.76	1.75	22637.87	22727.23	Std.cht	call	2006/2/23	15.95	0.322	4.06	2.29	18173.30	17695.95
	call	2005/4/11	3.69		0.90	0.84	22637.87	22727.23		call	2006/2/23	5.02		0.88	0.23	18173.30	17695.95
	put	2005/4/11	2.97		0.08	0.04	22637.87	22727.23		put	2006/2/23	10.92		5.45	4.92	18173.30	17695.95
Batob	call	2006/7/31	19.75	0.222	9.48	9.18	30510.89	30083.44	Std.cht	call	2006/7/31	19.45	0.313	12.76	13.18	19673.44	20217.04
	call	2006/7/31	5.05		1.30	1.05	30510.89	30083.44		call	2006/7/31	6.6		3.33	3.41	19673.44	20217.04
BG	call	2006/7/31	96.7	0.304	21.75	20.55	23357.59	23488.55	Tesco	call	2005/4/11	29.45	0.217	2.71	2.65	24928.69	24758.27
	call	2006/7/31	35.6		4.07	2.75	23357.59	23488.55		call	2005/4/11	6.53		0.31	0.31	24928.69	24758.27
BP	call	2005/4/11	40.25	0.235	5.73	5.02	125096.25	124837.90		put	2005/4/11	9.48		0.50	0.51	24928.69	24758.27
	call	2005/4/11	18.1		2.53	2.06	125096.25	124837.90	Vodafone	call	2005/4/11	9.48	0.235	0.74	0.68	90720.59	89706.38
	put	2005/4/11	27.4		1.45	1.00	125096.25	124837.90		call	2005/4/11	2.37		0.08	0.07	90720.59	89706.38
BP	call	2005/12/1	72.12	0.318	28.46	27.60	133097.36	132944.50		put	2005/4/11	3.82		0.23	0.27	90720.59	89706.38
	call	2005/12/1	22.94		4.63	4.56	133097.36	132944.50	Vodafone	call	2006/2/2	13.29	0.311	5.05	5.38	70249.17	71511.50
	put	2005/12/1	22.5		6.39	4.48	133090.90	132928.00		call	2006/2/2	7.25		2.15	2.18	70249.17	71511.50

BP	call	2006/2/23	51.11	0.280	15.98	12.50	128778.56	127957.40	Vodafone	call	2005/12/13	5.33	0.282	1.35	0.91	74977.68	75444.38
	call	2006/2/23	17.42		4.25	1.97	128778.56	127957.40		call	2005/12/13	1.63		0.32	0.13	74977.68	75444.38
	put	2006/2/23	54.26		21.69	21.24	128778.56	127957.40		put	2005/12/13	9.53		4.77	4.74	75361.97	75982.94
BP	call	2006/7/31	40.15	0.261	4.77	2.18	112301.38	113231.50	Vodafone	call	2006/8/	10.75	0.302	14.46	14.39	72419.40	72903.69
	call	2006/7/31	12.95		1.02	0.08	112301.38	113231.50		call	2006/8/	3.77		6.56	6.00	72419.40	72903.69
	put	2006/7/31	39.75		25.51	23.24	112301.38	113231.50		put	2006/8/	7.48		0.80	0.17	72145.23	72777.88
B.sky	call	2006/7/31	7.5	0.244	3.24	3.31	9598.75	9660.99	William Hill	call	2006/7/31	5.35	0.239	3.09	3.25	2258.15	2257.52
	call	2006/7/31	1.35		0.29	0.14	9598.75	9660.99		call	2006/7/31	1.76		0.76	0.74	2258.15	2257.52
BT	call	2005/4/11	14.4	0.223	1.94	1.95	18377.25	18559.04	Wpp	call	2006/7/31	6.85	0.251	5.49	5.01	8448.08	8290.59
	call	2005/4/11	6.3		0.73	0.75	18377.25	18559.04		call	2006/7/31	2.61		2.08	1.84	8448.08	8290.59
	put	2005/4/11	11.9		0.54	0.29	18377.25	18559.04	Hsbc	call	2006/3/1	3.82	0.216	0.94	0.67	109470.4	109716.20
BT	call	2006/7/31	25.85	0.260	30.86	29.28	23506.02	23506.08		call	2006/3/1	1.66		0.28	0.17	109427.5	109709.00
	call	2006/7/31	7.1		11.85	9.75	23506.02	23506.08		put	2006/3/1	5.79		1.84	2.17	10970.41	109716.20
Cable & wireless	call	2006/7/31	16.25	0.312	21.59	24.39	3649.04	3843.95	Hsbc	call	2006/7/31	7.05	0.217	2.36	3.08	109797.58	109155.40
	call	2006/7/31	7.45		13.30	14.95	3649.04	3843.95		call	2006/7/31	1.91		0.46	0.46	109797.58	109155.40
Centrica	call	2005/9/14	14.87	0.411	3.05	2.55	9302.02	9052.73		put	2006/7/31	3.52		0.88	0.84	109797.3	109113.15
	call	2005/9/14	25.13		8.97	11.02	9302.02	9052.73	Itv	call	2006/10/3	10.45	0.423	6.56	6.38	4225.92	4248.21
Diageo	call	2005/4/8	6.28	0.211	0.52	0.55	23654.68	23548.15		call	2006/10/3	5.45		2.68	2.45	4225.92	4248.21
	call	2005/4/8	1.82		0.10	0.12	23654.68	23548.15		put	2006/10/3	10.65		1.78	1.73	4225.92	4248.21
	put	2005/4/8	2.69		0.16	0.16	23654.68	23548.15	Land secs	call	2006/2/3	22.75	0.286	14.20	14.59	8703.91	8744.04
Glxsk	call	2006/7/31	8.4	0.260	2.17	1.33	81699.25	82018.94		call	2006/2/3	12.85		6.89	6.98	8703.91	8744.04
	call	2006/7/31	2.88		0.58	0.14	81699.25	82018.94	Legal&Gen	call	2005/4/11	11.18	0.266	0.59	0.63	7244.06	7221.61
	put	2006/7/31	9.5		3.35	3.53	81683.38	81932.66		call	2005/4/11	2.44		0.06	0.05	7244.06	7221.61
Hbos	call	2005/4/8	7.58	0.237	0.67	0.72	33011.64	33596.23		put	2005/4/11	5.43		0.50	0.46	7244.06	7221.61
	call	2005/4/8	2.73		0.15	0.15	33011.64	33596.23	Llds tsb	call	2006/2/23	38.06	0.341	10.21	7.55	29714.36	29599.95
	put	2005/4/8	3.26		0.22	0.14	33011.64	33596.23		call	2006/2/23	14.6		3.25	1.53	29714.36	29599.95
Hbos	call	2006/2/24	9.72	0.263	1.64	1.18	36718.36	36676.07		put	2006/2/23	68.68		24.01	24.81	29714.36	29599.95
	call	2006/2/24	2.37		0.27	0.17	36718.36	36676.07	Llds tsb	call	2006/7/31	44.55	0.285	30.00	30.20	31449.37	31557.33
	put	2006/2/24	6.34		3.57	3.93	36741.48	36690.03		call	2006/7/31	13.75		5.67	5.86	31449.37	31557.33
Hbos	call	2006/7/31	10.05	0.234	8.89	9.13	40723.29	40914.02		put	2006/7/31	39.55		6.77	5.61	31475.69	31585.49
	call	2006/7/31	2.4		2.13	2.23	40723.29	40914.02	Logiccmg	call	2006/7/31	25.65	0.382	11.38	11.05	2444.03	2626.23
Hsbc	call	2005/4/7	4	0.195	0.50	0.45	99246.21	99691.19		call	2006/7/31	11.35		3.15	3.43	2437.44	2624.31
	call	2005/4/7	2.12		0.24	0.25	99246.21	99691.19	M&S	call	2005/4/8	18.33	0.240	1.62	1.62	5796.55	5877.87
	put	2005/4/7	4.36		0.16	0.10	99292.48	99691.19		call	2005/4/8	4.84		0.27	0.25	5796.55	5877.87
										put	2005/4/8	24.93		1.52	1.27	5796.55	5877.87

3.2 Calculation of the Implied Stock Price

In order to conduct the SD test and the likelihood ratio efficiency test to compare the performance of the covered warrants prices and the underlying share prices, transformation of the covered warrants prices to equilibrium prices for their underlying shares is required. For this purpose, we apply the option-implied share price model proposed by Manaster and Rendleman (1982).

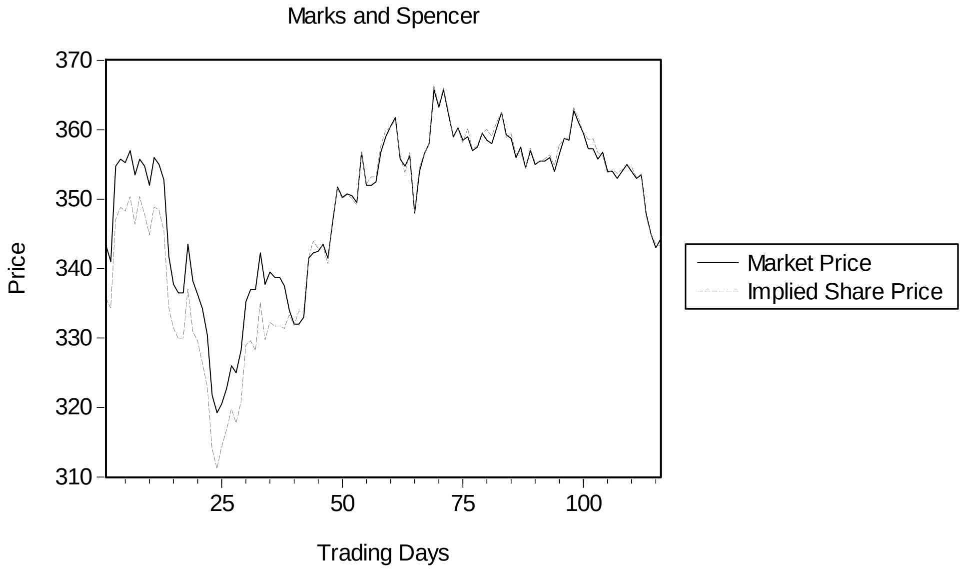
Manaster and Rendleman (1982) proposed the option-implied share price model to calculate the so-called implied share prices, S*, as well as the implied volatility. Our paper contributes by investigating the covered warrants' assessment of the equilibrium stock prices while preventing errors of measurement in terms of standard deviation. The implied volatility and prices are calculated simultaneously by including data from several covered warrants on the same underlying share that had identical duration and listing dates. [4]

The implied stock price, S_{it}*, and implied standard deviations, σ_{it}* for each pair *i* at time *t* can be calculated as:

$$(S_{it}^{*}, \sigma_{it}^{*}) = Arg \min_{S_{it}, \sigma_{it}} \sum_{j=1}^{N_{it}} [\ W^{j} - W^{j}(\ S_{it}, \sigma_{it})\ ]^{2}, \qquad (1)$$

where j denotes the covered warrant number. The solution to Equation (1) minimises the sum of the squared deviations between the observed and theoretical covered warrant prices, where *i* is the number of implied share price pairs (in total there are 71 pairs), S_{it} is the market share price, W^j is the observed covered warrant market prices, and $W^j(S_{it}, \sigma_{it})$ is the calculated theoretical covered warrants price. N_{it} represents the number of covered warrants used to compute the i^{th} implied price series at time *t*, where $j \geqq 2$, since at least two warrants are needed to find the argument minimum (Arg min). Since all covered warrants are associated with a share listed on the LSE, it is not necessary to mitigate the foreign exchange rate in our study. Moreover, since both the implied and actual share prices have similar tendencies and display overlapping patterns over the entire period, one could infer that the two financial instruments can be traded efficiently. In order to formally examine this inference, we employ the tests as discussed in the following subsections. Figure 1 exhibits the time series plots of sample trading days for the generated implied stock prices and the underlying share price series for Marks and Spencer and the Standard Chartered Bank, respectively.

Finally, to enhance the robustness of the estimation, several pricing models were adopted, including the Black-Scholes model, Hull and White's (1987) stochastic volatility model and Kou's Jump-Diffusion Model (1999). The computed implied prices are very close across all three employed models. The difference between the three models can only be observed in the implied volatility.



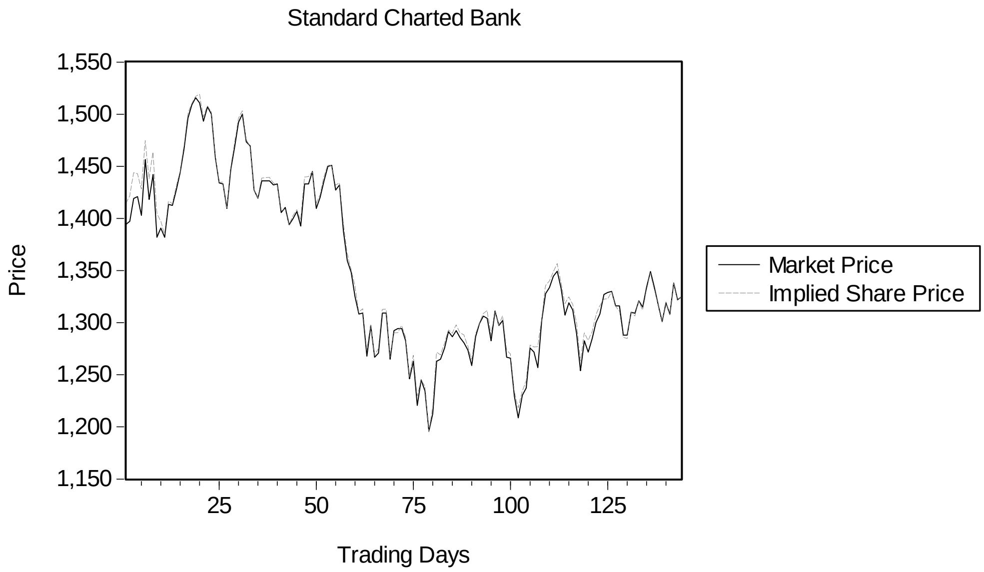


Figure 1
Implied Share Price vs. Actual Share Market Price

One can observe that the calculated implied share prices show a high degree of consistency with the actual underlying share market prices. This implies that the information contained in the implied share prices reflects that associated with the actual share market prices.

3.3 Stochastic Dominance Theory and Test

The next two sections describe stochastic dominance theory and the method of testing for SD.

Stochastic Dominance Theory

Stochastic dominance theory provides a general framework for ranking risky prospects based on utility theory. Hadar and Russell (1969), Hanoch and Levy (1969), Rothschild and Stiglitz (1970, 1971) and Whitmore (1970) lay the utility foundations of stochastic dominance analysis. Stochastic dominance rules are relevant for any well-defined von Neumann-Morgenstern (1944) set of utility functions. For example, stochastic dominance rules for risk averters, which apply to the general class of non-decreasing, concave utility functions, offer consistent rankings for all members of this class (Russell and Seo, 1978, 1989). Machina (1982), Starmer (2000), and Wong and Ma (2008) show that stochastic dominance criteria also apply for a range of non-expected utility theories of choice under uncertainty.

Let F and G be the cumulative distribution functions (CDFs), and f and g be the corresponding probability density functions (PDFs) of covered warrant implied share price W and its corresponding underlying share price, S, respectively, with common support $[a,b]$ where $a < b$. Let's Define:

$$H_0 = h,\ H_j(x) = \int_a^x H_{j-1}(t)\,dt \qquad \text{for } h = f, g;\ H = F, G \text{ and } j = 1,2,3.$$

The common SD rules define utility functions as FSD (First-order SD), SSD (Second-order SD), and the TSD (Third-order SD). Under FSD, investors are non-satiated (prefer more to less); under SSD, investors are non-satiated and risk-averse; under TSD, investors are non-satiated, risk-averse and possess decreasing absolute risk aversion (DARA). The SD rules are defined as follows (see Quirk and Saposnik, 1962; Fishburn, 1964; Hanoch and Levy, 1969):

Definition 1: *W dominates S by FSD (SSD, TSD), denoted by $W \succ_1 S$ ($W \succ_2 S$, $W \succ_3 S$) if and only if $F_1(x) \le G_1(x)$ ($F_2(x) \le G_2(x)$, $F_3(x) \le G_3(x)$) for all possible returns x lays between {a,b}, and the strict inequality holds for at least one value of x.*

Note that there is a hierarchical relationship between the orders of SD: FSD implies SSD and TSD, but the converse is not true. According to the conventional theories of market efficiency, the market is considered to be inefficient if one is able to earn an abnormal return. The criteria that FSD employs are whether investors could increase their expected wealth or utility by switching their investment choice from underlying shares (S) to W (covered warrants) or vice versa regardless their specific preferences. Studies by Jarrow (1986) and Falk and Levy (1989) claim that if FSD exists, under certain conditions arbitrage opportunities also exist; as such, investors will increase their wealth and expected utility if they shift from holding the dominated asset to the dominant one, and thus the market is inefficient. Wong et al. (2008) claim that even if FSD exists statistically, arbitrage opportunities may not exist; however, investors can increase their expected wealth as well as their expected utility if they shift from holding the dominated asset to the dominant one.

Under SSD, if W dominates S, there is no abnormal profit obtained by switching from S to W; however, switching would allow risk-averse investors to have preference and increase their expected utility. In this scenario, we claim that there maybe no arbitrage opportunity and the market is inefficient if all investors are risk averse.

The TSD criterion, which assumes that all investors' utility functions exhibit non-satiation, risk aversion, and DARA, means if W dominates S by TSD, it can be claimed that the market is inefficient if investors are associated with risk aversion and DARA. One would not make an expected utility by switching from S to W, even though switching would allow risk-averse DARA investors to increase their expected utility.

Stochastic Dominance Test

Early work on applying SD to examine asset performance includes Porter and Gaumnitz (1972), Porter (1973), and Beach and Davidson (1983). More recently, Isakov and Morard (2001) have employed SD to investigate the performance of a global investment strategy that combined diversification and option strategies, whereas Antoniou et al. (2009) have applied SD to examine the performance of international portfolio diversification and homemade portfolios. While both these studies result in useful analyses through employing the SD theory, they do not perform SD tests to examine the preference and the expected utility gained by the risk-averse investors while making investment decisions.

There are two major classes of SD tests, one is to make comparison of the distributions at a finite number of grid points (see, for example, Anderson, 2004; Xu, 1997; and Davidson and Duclos (DD test), 2000, Tse and Zhang (2004) and Lean et al. (2008)). The other class proposes the use of infimum or supremum statistics in support of the distributions (see, for example, McFadden, 1989; Kaur et al., 1994; Barrett and Donald, 2003; and Linton et al., 2005).

In this paper, the Davidson and Duclos (DD test) is presented as follows and the results of LMV test (Linton et al., 2005), which applies the bootstrap procedure to find close critical value, are also available upon request. [5]

Consider a sample set { y_i } of N_w observations, i = 1, 2… N_w from a population of covered warrants implied share prices, W , with cumulative density distribution function F_W , and further consider a sample set { z_i } of N_S observations, i = 1, 2… N_s from the population of underlying shares S with cumulative density distribution function F_S . [6] Define $D_W^1(x) = F_W(x)$ and let $D_w^j(x) = \int_0^x D_w^{j-1}(u)du$ for any integer $j \geq 2$. $D_S^j(x)$ is defined similarly. W is said to dominate S stochastically at order j $(j = 1,2,3)$, denoted by $W \succ_j S$, if $D_S^j(x) \geq D_W^j(x)$ for all x, with strict inequality for some $x \in \Re$. As W and S are correlated and N_w = N_s = N, let (y_i , z_i) be a paired observation for any i. For j=1, 2, and 3, consider the following DD statistic (Davidson and Duclos, 2000):

$$T^j(x) = \frac{\hat{D}_W^j(x) - \hat{D}_S^j(x)}{\sqrt{\hat{V}^j(x)}}, \qquad (2)$$

where $\hat{V}^j(X) = \hat{V}_w^j(X) + \hat{V}_s^j(X)$,

$$\hat{D}_w^j(X) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x - y_i)_+^{j-1}$$

$$\hat{D}_s^j(X) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x - z_i)_+^{j-1}$$

$$\hat{V}_w^j(X) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x - y_i)_+^{2(j-1)} - \hat{D}_w^j(X)^2\right]$$

$$\hat{V}_s^j(X) = \frac{1}{N}\left[\frac{1}{N((j-1)!)^2}\sum_{i=1}^{N}(x - z_i)_+^{2(j-1)} - \hat{D}_s^j(X)^2\right]$$

A multiple comparison test based on the procedure proposed by Bishop, Formby and Thistle (BFT, 1992) is adopted. Fong et al. (2005) and others recommend following BFT by considering the fixed values $x_1, x_2, \ldots, x_i, \ldots, x_I$ and applying the corresponding statistics $T^j(x_i)$ for $i = 1, 2, \ldots, I$ *at each grid point* to test the following hypotheses:

$$H_0: D_s^j(x_i) = D_w^j(x_i), \text{ for all } x_i;$$
$$H_A: D_s^j(x_i) \neq D_w^j(x_i), \text{ for some } x_i;$$
$$H_{A1}: D_s^j(x_i) \leq D_w^j(x_i), \text{ for all } x_i; D_s^j(x_i) < D_w^j(x_i) \text{ for some } x_i; \text{ and}$$
$$H_{A2}: D_s^j(x_i) \geq D_w^j(x_i), \text{ for all } x_i; D_s^j(x_i) > D_w^j(x_i) \text{ for some } x_i.$$

To control for the probability of rejecting the overall null hypothesis, BFT suggest the use of the studentized maximum modulus distribution, M_∞^I, with infinite degrees of freedom. $M_{\infty,\alpha}^I$ is the (1-α) percentile of M_∞^I. According to the BFT, the null hypothesis H_0 is rejected when::

$$\max_{i \leq I} \left| T_j(x_i) \right| > M_{\infty,\alpha/2}^I, \text{ for the alternative } H_A;$$
$$\max_{i \leq I} T_j(x_i) < -M_{\infty,\alpha}^I, \text{ for the alternative } H_{A1}; \text{ and}$$
$$\max_{i \leq I} T_j(x_i) > M_{\infty,\alpha}^I, \text{ for the alternative } H_{A2}.$$

The DD test compares the distributions at a finite number of grid points. Consulting too few grid points will lead to insufficient information regarding the distributions between any two consecutive grids (Barrett and Donald 2003), while too many grid points will violate the independence assumption required by the SMM distribution (Richmond 1982). Various studies have examined the choice of grid points (see, for example, Tse and Zhang, 2004; and Lean et al., 2008). Fong et al. (2005), Gasbarro et al. (2007), and many others suggest using 10 major partitions and 10 minor partitions within any two consecutive major partitions for each comparison made, and the statistical inference based on $M_{\infty,\alpha}^I$ with I =10 is drawn.[7] To minimize Type II errors and avoid almost-SD (Leshno and Levy 2002), we use a 5% cut-off point for the estimation of the test statistic in our statistical inference to avoid the problem of almost SD.[8] We also apply the approach recommended by Bai et al. (2009) to use simulated critical values and maximum values of the test statistics in our analysis.

3.4 The Informational Efficiency Test of the Covered Warrants Market

In this paper, we complement the SD test by providing an alternative method to test the hypothesis of informational efficiency in the UK covered warrants market—the GARCH model including the warrant implied volatility in the variance equation and the corresponding likelihood ratio test proposed by Xu and Taylor (1995) and Claessen and Mittnik (2002).

First, we estimate the GARCH (1,1)-IV model with GED distribution, in which the IV factor representing the implied volatility is derived from the covered warrant prices via the Black-Scholes model. Second, we apply the LR test through a bootstrapping procedure to examine the significance of the IV factor under the constraint that other variables in the GARCH variance equation are zero. If the covered warrants market performs efficiently, the null hypothesis is not rejected, indicating that the covered warrant prices offer optimal one-period-ahead volatility.

It should be noted that the asymptotic version of the LR test cannot be used, since for small sample sizes (frequently encountered in the case of warrants), the asymptotic approximation of the test statistic distribution is often very far from the true finite sample test statistic distribution, which leads to an over-rejection of the null hypothesis (see remarks in Table 3). The bootstrap approximation of the test statistic distribution is much closer to the true finite sample distribution, and its results are much more reliable.

The GARCH(1,1)-IV model

This model consists of information contained in the past returns of both stock prices and covered warrant prices by adding an exogenous implied volatility (IV) variable to the GARCH model (see, for example, Day and Lewis, 1992; Lamoureux and Lastrapes, 1993; Xu and Taylor, 1995; and Claessen and Mittnik, 2002). Following Claessen and Mittnik's (2002) application of the model, we adopt the following specifications:

$$R_t = \mu + \alpha R_{t-1} + \varepsilon_t,$$

$$\varepsilon_t \sim GED(0,\sigma_t^2),$$

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2 + \gamma\, IV_{t-1}^2, \qquad (3)$$

where R_t is the share return at day *t*, the GED is the generalized error distribution (Taylor, 1994),[9] the variance forecast in equation (3) is similar to that of the pure GARCH case, and the difference is the addition of $\gamma\, IV_{t-1}^2$ in the forecasting recursion. Within the GED distribution, let *r* be the tail parameter, which is always positive. The GED is a Gaussian distribution when *r* =2, and is fat-tailed if r is less than 2. Through this framework, the informational efficiency hypothesis can be examined in a way such that if the constraints $\alpha = \beta = 0$ in equation (3) are not rejected, its form can then be reduced to the following equation:

$$\sigma_t^2 = \omega + \gamma\, IV_{t-1}^2, \qquad (4)$$

and the null hypothesis of market efficiency is thereby not rejected.[10]

The likelihood ratio test

To test the null hypothesis of $\alpha = \beta = 0$ in equation (3), we follow Xu and Taylor (1995) to employ the likelihood ratio test statistic $LR = 2(L_0 - L_1)$, in which L_0 and L_1 are the maximum log-likelihoods for equations (3) and (4), respectively. If the null hypothesis is not rejected, the test statistic $LR = 2(L_0 - L_1)$ is distributed as the χ_2^2 distribution. To conduct the test, we impose a value of *r* (the GED parameter) to estimate the non-converged samples and propose to re-compute the critical value by using the bootstrap procedure.[11] A bootstrap LR test is developed as follows:

1. The *LR* test statistic is computed on the pair (underlying returns, IV) from equations (3) and (4). The model is estimated under the null hypothesis of efficiency ($\alpha = \beta = 0$) in the variance equation using the observations for each underlying return series and implied volatilities obtained from the corresponding warrants.
2. The estimated parameters are used to generate B simulated series r_t^b (b=1, …, B) under the null hypothesis as follows:

$$r_t^b = \mu + \rho\, r_{t-1}^b + \varepsilon_t^b,$$

$$\varepsilon_t^b \sim GED(0, \left(\sigma_t^b\right)^2),$$

$$\left(\sigma_t^b\right)^2 = \omega + \gamma\, IV_{t-1}^2 ,$$

   where IV_t is the original series, $r_1^b = r_1$, and μ, ρ, ω, and γ are the estimated parameters under the null for b=1, …, *B*, with *B* set to be large.
3. For each simulated series, the LR test is applied to get a bootstrap replication, LR^b, of the statistic.
4. The bootstrap p-value is then computed, where

$$p = \frac{1}{B}\sum_{b=1}^{B} LR^b > LR.$$

5. If $p < 0.05$, the null hypothesis of efficiency is rejected and vice versa.

4. Empirical Results and Analysis

4.1 Stochastic Dominance Results

We first examine whether there is any stochastic dominance (SD) relation between the 71 pairs of covered warrants implied share prices(W) and the corresponding underlying share prices (S) using the DD test, as discussed in the above section. Since the findings across these 71 pairs are qualitatively the same, we only display the detailed results for the UK list code M&S 0213 here. The plots of the estimated empirical cumulative distribution functions of W and S are exhibited in Figure 2, and the plots of their corresponding DD statistics for the entire range are shown in Figure 3.

From Figure 2, the CDF for W and the CDF for S are found to be very similar. That said, the empirical CDF of S is clearly greater than that of W from the 51st interval to the 58th interval (returns from 0.18% to 0.40%) and from the 67th interval to the 77th interval (returns from 0.68% to 1%), respectively.

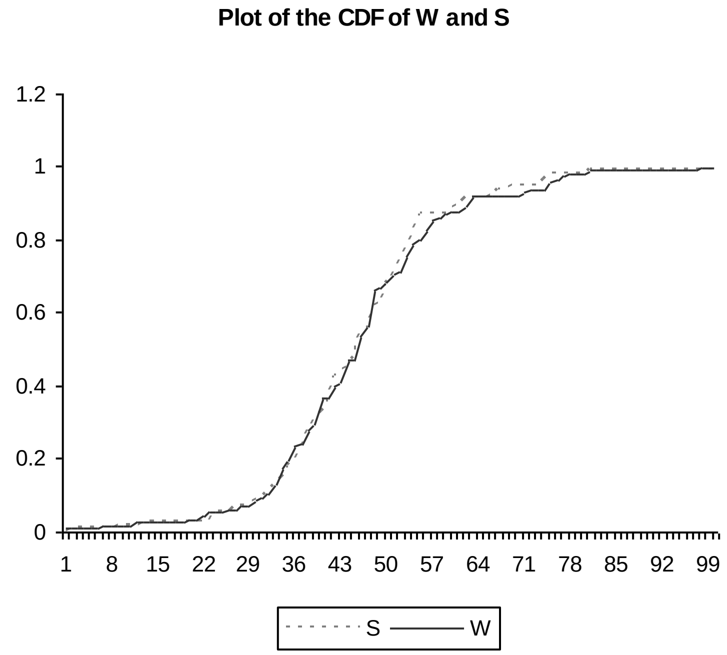


Figure 2
Plots of the CDFs for W and S
From Figure 2, the CDF for W and the CDF for S are found to be very similar. That said, the empirical CDF of S is clearly greater than that of W from the 51st interval to the 58th interval (returns from 0.18% to 0.40%) and from the 67th interval to the 77th interval (returns from 0.68% to 1%), respectively.

Figure 3 shows that the DD statistics for all three orders are within the two dashed lines, which represent the critical values of -3.254 and 3.254, respectively. This implies that neither W nor S stochastically dominate each other in the sense of FSD, SSD or TSD.

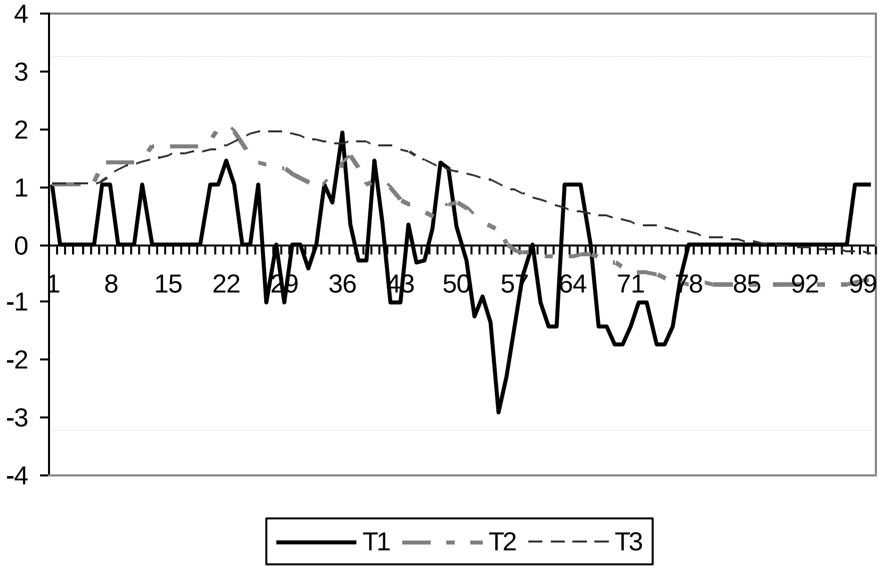


Figure 3
Plots of the Davidson-Duclos Statistics (DD statistics)

Figure 3 shows that the DD statistics for all three orders are within the two dashed lines, which represent the critical values of -3.254 and 3.254, respectively. This implies that neither W nor S stochastically dominates each other in the sense of FSD, SSD or TSD.

In Figure 3, the estimated DD statistics for all three orders are reported, i.e., T1, T2, and T3. As one can observe, the plot of T1 shows that in the above-mentioned two regions, investors prefer W to S in the sense of first-order stochastic dominance (FSD). To investigate whether there is a stochastic dominance relationship between W and S in the sense of higher order stochastic dominance, it is useful to recall that W is preferable to S in the presence of second-order stochastic dominance (SSD) if and only if the expected utility of W will be higher than the expected utility of S for any risk-averse investor, and W is preferable to S in the presence of third-order stochastic dominance (TSD) if and only if the utility of W will be higher than the utility of S for any risk-averse investor exhibiting decreasing absolute risk aversion. The region of possible dominance results between W and S in the sense of SSD and TSD are clear, since there is only one change in sign. Figure 3 shows that S is likely to be preferred to W over the first 55 percentiles (returns from -1.39% to 0.31%) of the SSD test and over the first 86 percentiles (returns from -1.39% to 1.28%) of the TSD test, while W is likely to be preferred to S over the remainder of the distribution.

However, to formally examine whether there is any stochastic dominance over the whole sample, stringent statistical tests are required. Figure 3 shows that the DD statistics for all three orders are within the two dashed lines, which represent the critical values of -3.254 and 3.254, respectively. This implies that neither W nor S

stochastically dominate each other in the sense of FSD, SSD or TSD.[12]

In Table 2, we report the results of max $T^j(x_i)$ and min $T^j(x_i)$ for all pairs and for j=1, 2, and 3 in Table 2. Since $\left|\max T^j(x_i)\right|$ ($\left|\min T^j(x_i)\right|$) is less than 3.254, the critical value for $\alpha = 0.05$ for all pairs except one (pair code "Partygaming")[13], we do not reject the null hypothesis that $\mathrm{H_0 : D_s^j(x_i) = D_w^j(x_i)}$, for all $\mathrm{x_i}$. This suggests that (1) there is no arbitrage opportunity between covered warrants and their underlying stocks, (2) the covered warrant and its underlying stock do not dominate each other, and (3) the hypothesis that the cumulative distributions of the covered warrant and its underlying stock are identical is not rejected. Further, neither of the following are rejected based on these findings: (1) any investor who prefers more to less will be indifferent between investing in the covered warrant and investing in its underlying stock, and (2) the covered warrant and its underlying stock are efficient and the investors in these markets are rational.

Table 2: Results for the Davidson-Duclos (DD) Test Statistics

This table reports the maximum and minimum of the Davidson-Duclos test statistics, T1, T2 and T3, for the three orders of the covered warrants and their corresponding stocks. Readers may refer to Equation (2) for the definitions of T1, T2 and T3.

Pair			T1	T1	T2	T2	T3	T3
Ang amer	Max	(Min)	2.289	(-1.756)	0.672	(-1.484)	0.232	(-1.396)
Angamer	Max	(Min)	1.912	(-2.027)	-0.151	(-1.272)	-0.656	(-1.159)
Antofaga	Max	(Min)	2.375	(-2.142)	2.107	(-0.277)	1.76	(-0.507)
Arm	Max	(Min)	2.708	(-1.92)	0.59	(-1.437)	0.12	(-1.113)
Astrazen	Max	(Min)	2.027	(-1.749)	1.571	(-0.176)	1.119	(-0.407)
AsZen	Max	(Min)	1.433	(-1.144)	1.433	(-0.238)	1.43	(-0.742)
Aviva	Max	(Min)	1.688	(-1.427)	0.946	(-0.89)	0.723	(-0.993)
Azen	Max	(Min)	2.277	(-2.029)	1.783	(-0.9)	1.357	(-0.387)
Bae	Max	(Min)	1.523	(-1.755)	-0.277	(-1.077)	-0.567	(-1.004)
Barclays	Max	(Min)	1.687	(-2.036)	1.367	(-0.504)	1.255	(-0.243)
Barclays	Max	(Min)	1.433	(-2.779)	1.093	(-0.709)	1.013	(-0.255)
Barclays	Max	(Min)	1.003	(-1.683)	-0.152	(-1.666)	-0.657	(-1.419)
Barclays	Max	(Min)	2.026	(-2.905)	1.465	(-1.003)	1.121	(-1.003)
Batb	Max	(Min)	1.523	(-2.036)	0.142	(-1.423)	-0.539	(-1.414)
Batob	Max	(Min)	2.026	(-1.808)	1.423	(-0.952)	1.423	(-0.58)
Bg	Max	(Min)	1.752	(-2.031)	0.459	(-1.218)	-0.009	(-1.414)

Bg	Max	(Min)	3.1	(-2.713)	2.527	(-0.07)	2.299	(-1.004)
Bg	Max	(Min)	2.027	(-1.424)	1.638	(-0.047)	1.472	(-0.746)
Bp	Max	(Min)	1.755	(-1.427)	0.493	(-1.12)	0.151	(-0.865)
Bp	Max	(Min)	2.315	(-1.433)	1.948	(-0.074)	1.71	(-0.616)
Bp	Max	(Min)	1.75	(-2.144)	1.073	(-1.424)	0.424	(-1.424)
Bp	Max	(Min)	1.749	(-1.912)	1.343	(-1.337)	1.16	(-0.827)
British Airt	Max	(Min)	3.076	(-2.781)	1.003	(-1.671)	1.003	(-1.022)
Bsb	Max	(Min)	1.652	(-1.755)	0.407	(-1.004)	-0.036	(-1.004)
BSy	Max	(Min)	2.781	(-2.35)	1.412	(-1.541)	1.419	(-1.09)
Bt	Max	(Min)	1.004	(-1.221)	1.004	(-0.002)	1.004	(-0.632)
Bt	Max	(Min)	2.918	(-2.142)	-0.422	(-1.851)	-0.895	(-1.613)
Cable and wireless	Max	(Min)	2.737	(-2.615)	0.621	(-2.834)	-0.368	(-2.717)
Centrica	Max	(Min)	1.521	(-2.508)	1.004	(-2.206)	1.004	(-1.769)
Glaxo	Max	(Min)	1.912	(-1.966)	2.035	(-0.414)	1.786	(-0.021)
Glxsk0	Max	(Min)	1.433	(-2.315)	1.424	(-0.495)	1.282	(-0.155)
HBOS	Max	(Min)	1.424	(-2.277)	1.316	(-1.106)	1.118	(-0.178)
HBOS	Max	(Min)	2.026	(-2.217)	-0.435	(-1.631)	-1.003	(-1.193)
HBOS	Max	(Min)	2.036	(-2.036)	1.853	(-1.004)	1.77	(-1.004)
HSBC	Max	(Min)	2.182	(-2.164)	1.361	(-0.913)	1.08	(-0.983)
HSBC	Max	(Min)	3.102	(-2.504)	2.696	(-0.392)	2.564	(-0.701)
HSBC	Max	(Min)	2.142	(-1.424)	1.606	(-1.003)	1.289	(-1.003)
Itv	Max	(Min)	2.939	(-2.939)	-0.133	(-2.518)	-0.736	(-2.296)
Land secs	Max	(Min)	1.912	(-2.365)	1.003	(-1.563)	1.003	(-1.268)
Legal and general	Max	(Min)	2.153	(-2.731)	1.004	(-0.775)	1.004	(-0.297)
Lloyd	Max	(Min)	2.142	(-2.905)	0.433	(-1.003)	-0.046	(-1.003)
Llyds	Max	(Min)	1.139	(-2.786)	-0.445	(-1.122)	-0.773	(-1.075)
LoCMG	Max	(Min)	2.905	(-2.027)	1.535	(-1.003)	0.885	(-1.003)
M&S	Max	(Min)	1.92	(-2.932)	2.044	(-0.701)	1.937	(-0.173)
M&S	Max	(Min)	2.153	(-1.908)	1.003	(-1.211)	1.003	(-0.116)
National grid	Max	(Min)	2.026	(-1.92)	0.238	(-1.468)	-0.257	(-1.117)
Partygaming	Max	(Min)	3.606	(-2.904)	2.469	(-0.003)	1.918	(-1.003)
Person	Max	(Min)	2.036	(-2.932)	-0.361	(-1.255)	-0.822	(-1.015)
Prudential	Max	(Min)	2.286	(-2.153)	2.142	(-0.807)	1.697	(-0.102)
Prudential	Max	(Min)	3.156	(-3.1)	3.094	(-0.008)	2.813	(-1.004)
Prudential	Max	(Min)	2.027	(-2.153)	0.996	(-1.649)	0.526	(-1.003)
RBS	Max	(Min)	1.424	(-2.376)	1.236	(-0.536)	1.083	(-0.71)
Reuters	Max	(Min)	1.427	(-2.286)	1.004	(-1.095)	1.004	(-0.655)
Reuters	Max	(Min)	1.004	(-1.004)	1.004	(-0.003)	1.004	(-0.63)
Rio tino	Max	(Min)	1.749	(-2.152)	1.713	(-1.21)	1.045	(-1.003)
Rio tino	Max	(Min)	2.499	(-1.424)	1.003	(-1.181)	1.003	(-1.044)
Rio tinto	Max	(Min)	1.768	(-1.768)	1.007	(-1.052)	1.007	(-0.903)
Rolls Royce	Max	(Min)	2.968	(-1.912)	0.947	(-1.426)	1	(-1.357)

Reuters	Max	(Min)	2.737	(-1.647)	0.277	(-1.035)	-0.268	(-1.003)
Saga	Max	(Min)	1.427	(-2.736)	1.275	(-1.125)	0.881	(-1.005)
Shire	Max	(Min)	2.027	(-1.749)	0.548	(-2.425)	0.143	(-1.724)
Smith	Max	(Min)	1.647	(-1.749)	0.816	(-1.919)	0.039	(-1.786)
Stand chart	Max	(Min)	2.549	(-2.708)	0.274	(-2.746)	-0.716	(-2.33)
Standard Charted bank	Max	(Min)	2.713	(-1.648)	0.435	(-1.988)	-0.319	(-1.831)
Tesco	Max	(Min)	1.928	(-2.571)	0.082	(-2.077)	-0.781	(-1.694)
Vodafone	Max	(Min)	2.165	(-2.417)	1.679	(-0.113)	1.63	(-0.774)
Vodafone	Max	(Min)	2.567	(-1.436)	0.693	(-1.347)	0.172	(-1.115)
Vodafone	Max	(Min)	1.47	(-2.497)	1.003	(-0.503)	1.003	(-0.162)
Vodafone	Max	(Min)	1.717	(-2.28)	-0.114	(-2.042)	-0.55	(-1.837)
William hill	Max	(Min)	1.908	(-1.617)	0.505	(-1.003)	0.379	(-1.003)
Wpp	Max	(Min)	2.142	(-1.511)	0.56	(-1.996)	0.05	(-1.804)

4.2 The Informational Efficiency Test Result

Table 3 presents the empirical results of the informational efficiency test; a bootstrap LR test is derived to examine the null hypothesis that the market performs efficiently. The data are estimated under an AR(1)-GARCH(1,1)-GED(*r*) specification, where *r* is the GED parameter that makes the distribution non-Gaussian (it is Gaussian if *r*=2). The LR test statistic is presented, such that *r* presents the value for the GED parameter. The bootstrap P value is computed using the bootstrap distribution. At least B=99 bootstrap replications are used to compute the bootstrap P value. Number (#) of Imposing *r*: depending on the estimated value for *r* under the null, the bootstrap procedure can encounter computational problems. If *r* is smaller than 1 or greater than 4 (which is unrealistic), *r* is fixed to 1 or 4, respectively. If the bootstrap estimates under the null hypothesis are computationally difficult, the value of *r* is also fixed to the original estimated value for *r* under the null hypothesis. * denotes significance at the 5% level (p value < 0.05). The final row provides the rate of rejection of the null hypothesis of market efficiency. In sum, 52 of 71 (75%) samples confirm the null hypothesis that the prices of covered warrants already efficiently reflect past returns information in the underlying share prices. This finding is consistent with results obtained using the SD tests: none of the financial instruments dominate the others, and hence there is no risk premium. For the asymptotic test, the rate of rejection is 95%, which is over-estimated. However, it is well known that the asymptotic test over-rejects the null hypothesis, since the true finite distribution of the LR statistics is far from its asymptotic approximation. For the bootstrap test, the rate is 25%. Firstly, a large improvement of the P value can be observed by using bootstrap techniques rather than the asymptotic approximation. Secondly, we can conclude that the market is efficient for most of the series.

Table 3. Bootstrap LR Test

Table 3 presents empirical results of the informational efficiency test. A bootstrap LR test is developed to examine the null hypothesis that the market demonstrates information efficiency (H_0: Market demonstrates information efficiency). The data are estimated under an AR(1)-GARCH(1,1)-GED(*r*) specification, where *r* is the GED parameter that makes the distribution non-Gaussian (it is Gaussian if *r*=2). For the bootstrap procedure, see subsection 3.2.2.2.

In the table, pair specifies the name of the underlying share – implied price (implied from the warrants) pair, statistic presents the LR test statistic, and *r* presents the value for the GED parameter. The bootstrap P value is computed using the bootstrap distribution. At least B=99 bootstrap replications are used to compute the bootstrap P value. # Imposing *r*: depending on the estimated value for *r* under the null, the bootstrap procedure can encounter computational problems. If *r* is smaller than 1 or greater than 4 (which is unrealistic), *r* is fixed to 1 or 4, respectively. If the bootstrap estimates under the null hypothesis are computationally difficult, the value of *r* is also fixed to the original estimated value for *r* under the null hypothesis. * denotes significance at the 5% level (p value < 0.05). The final row provides the rate of rejection of the null hypothesis of market efficiency. In sum, 52 of 71 (75%) samples confirm the null hypothesis that the prices of covered warrants already efficiently reflect past returns information in the underlying share prices. This finding is consistent with results obtained using the SD tests: none of the financial instruments dominate the others, and hence there is no risk premium. For the asymptotic test, the rate of rejection is 95%, which is over-estimated. However, it is well known that the asymptotic test over-rejects the null hypothesis, since the true finite distribution of the LR statistics is far from its asymptotic approximation. For the bootstrap test, the rate is 25%. Firstly, a large improvement of the P value can be observed by using bootstrap techniques rather than the asymptotic approximation. Secondly, we can conclude that the market is efficient for most of the series.

Bootstrap LR test				Bootstrap LR test			
Pair	**Statistic**	***r***	**P value (B=99)**	**Pair**	**Statistic**	***r***	**P value (B=99)**
Ang amer	22.12	4.00 #	0.15	HSBC	42.05	1.33	0.61
Ang amer	373.6	1.00 #	0.53	Itv	56.05	2.55	0.34
Antofaga	57.65	4.00 #	0.01 *	Land secs	37.28	1.47	0.73
Arm	1122.94	1.00 #	0.96	Legal and general	234.55	1.00 #	0.97
Astrazen	228.53	4.00 #	0.00 *	Lloyd	62.63	1.82	0.06
AsZen	29.25	3.01 #	0.02 *	Llyds	11.55	1.27	0.46
Aviva	9.17	2.5	0.83	LoCMG	33.17	0.99	0.77
Azen	55.64	0.95	0.49	M&S	48.08	1.66	0.54
Bae	28.18	1.51	0.74	M&S	15.49	0.99	?
Barclays	16.16	1.92 #	0.41	National grid	37.1	1.81	0.26
Barclays	12.56	3.36 #	0.19	Partygaming	717.33	1.00 #	0.92
Barclays	51.99	2.50 #	0.04 *	Person	33.09	1.23	0.51
Barclays	17	3.49	0.48	Prudential	43.56	1.57	0.34
Batb	381.66	4.00 #	0.04 *	Prudential	55.97	3.94	0.08
Batob	9.25	3.55	0.68	Prudential	13.17	2.89	0.8
Bg	86.61	4.00 #	0.00 *	RBS	16.91	3.43 #	0.42
Bg	822.84	1.00 #	0.00 *	Reuters	32.1	2.1	0.4
Bg	69.18	1.64	0.34	Reuters	19.21	1.42	0.64
Bp	9.04	2.03	0.45	Rio tino	18.98	2.05	0.32
Bp	487.84	1.00 #	0.9	Rio tino	1083.96	1.00 #	0.79

Bp	294.37	1.00 #	1	Rio tinto	13.62	2.48 #	0.04 *
Bp	5.36	2.08	0.83	Rolls Royce	27.36	3.13	0.02 *
British Air	3.89	1.14	0.61	Reuters	104.2	1.41	0.33
Bsb	36.73	4.07	0.2	Saga	7.05	1	0.96
BSy	36.9	0.76	0.46	Shire	212.12	2.23	0.00 *
Bt	59.49	1.41	0.18	Smith group	162.65	2.73	0.00 *
Bt	15.82	2.35	0.11	Stand chart	11.27	3.04	0.77
Cable and wireless	4.94	2.14	0.75	standard charted bank	419.22	1.00 #	1
Centrica	107.55	2.13	0.08	Tesco	55.48	4.00 #	0.19
Glaxo	89.27	2.53 #	0.02 *	Vodafone	0.55	1.2	0.98
Glxsk0	58.02	4.00 #	0.00 *	Vodafone	11.17	1.00 #	0.09
HBOS	1050.55	1.00 #	0.00 *	Vodafone	6.45	1.28	0.52
HBOS	84.46	3.72	0.15	Vodafone	19.85	3.42 #	0.09
HBOS	92.79	4.00 #	0.00 *	Willam hill	187.06	4.00 #	0.01 *
HSBC	40.19	1.01	0.24	Wpp	30.38	1.52	0.68
HSBC	72.22	4.00 #	0.01				
Rejection rate of H_0 at 5% significance level:					**0.25**		

5. Conclusions

This paper contributes to the existing literature by adopting a stochastic dominance approach to examine the dominated / dominant relation between UK covered warrants and their underlying shares. The paper also contributes by outlining a method to directly retrieve implied share prices from covered warrant market prices, without borrowing information from other derivatives or stock options. The stochastic dominance approach implements the expected utility model and studies the return distribution directly. A bootstrap LR test is further developed to enhance the robustness of the empirical findings from the SD test.

Overall, the empirical results show that the UK covered warrants market and its corresponding underlying stock market do not dominate each other to any degree. Further, there are no arbitrage opportunities: these markets are efficient. Considering the features of this market—specifically that UK covered warrants and their underlying shares are traded synchronously on the same platform—we believe our findings to be reasonable. Identical trading venues and trading hours improve information transparency, which in turn reduces transaction costs and makes the market more efficient. Therefore, we conclude that the UK covered warrants market plays an informative role. As such, both practitioners and scholars may consult this study a reference for further research into derivatives trading.

References:

Abad, D., Nieto, B., 2007. The Unavoidable Task of Understanding Warrants Pricing. working paper.

Aitken, M, Harris, F. H. deB., Mclnish, T. H., Segara, R., 2010. Are third-party equity warrants redundant? Cass-Capco Institute Paper series on risk Journal. 22, 153-161

Aitken, M. and Segara, R., 2005. Impact of warrant introductions on the behaviour of underlying0 stocks: Australian evidence, Accounting and Finance. 45, 127-144.

Anderson, G. J., 2004. Toward an empirical analysis of polarization. Journal of Econometrics. 22, 1-26.

Antoniou, A., Olusi, O., Paudyal, K., 2009. Equity home-bias: A suboptimal choice for UK investors? European Financial Management. 10, 1-31.

Bai, Z., Hua, L., Wong, W.K., 2009. A Note on the Stochastic Dominance Test Statistics. Social Science Research Network Working Paper Series 1424390.

Baillie, R.T., Bollerslev, T., 1989. The message in daily exchange rates: A conditional variance tale. J Bus Econ Stat. 7, 297-305.

Barrett, G.F., Donald, S.G., 2003. Consistent tests for stochastic dominance. Econometrica. 71, 71-104.

Bartram, S.M., Fehle, F., 2007. Competition without Fungibility: Evidence from Alternative Market Structures for Derivatives. Journal of Banking and Finance. 31, 659-677.

Beach, C.M., Davidson, R., 1983. Distribution-free statistical inference with Lorenz curves and income shares. The Review of Economic Studies. 50, 723-735.

Biais, B., Hillion, P., 1994. Insider and liquidity trading in stock and options markets. Review of Financial Studies. 7, 743-780.

Bishop, J.A., Formby, J.P., Thistle, P.D., 1992. Convergence of the South and non-South income distributions. American Economic Review. 82, 262-272.

Black. F., 1975. Fact and fantasy in the use of options. Financial Analysts Journal. 31, 36-41.

Chan, H.W.H., Pinder, S.M., 2000. The value of liquidity: evidence from the derivatives market. Pacific-Basin Finance Journal. 8, 483-503.

Chiras D. P., Manaster S., 1978, The information content of option prices and a test of market efficiency Journal of Financial Economics. 6, 213-234.

Claessen, H. Mittnik, S., 2002. Forecasting stock market volatility and the informational efficiency of the DAX-index options market. European Journal of Finance. 8, 302-321.

Cox, C. C., 1976. Futures trading and market information. Journal of Political Economy. 48, 1215-1237.

Davidson, R., Duclos, J. Y., 2000. Statistical inference for stochastic dominance and for the measurement of poverty and inequality. Econometrica. 68, 1435-1464.

Day, T. E., Lewis, C. M., 1992. Stock market volatility and the information content of stock index options. Journal of Econometrics. Vol. 52, 267-87.

Diltz, J. D., Kim, S., 1996. The relationship between stock and options price changes. Financial Review. 31, 499-519.

Engle, R. F., Bollerslev, T., 1986. Modeling the persistence of conditional variances. Econometric Reviews. 5, 1-50.

Falk, H., Levy, H., 1989. Market reaction to quarterly earnings' announcements: A stochastic dominance based test of market efficiency. Management Science. 35, 425-446.

Figlewski, T. J., 1981. Futures trading and volatility in the GNMA market. Journal of Finance. 36, 445-456.

Fishburn, P. C., 1964. Decision and Value Theory. Wiley, New York.

Fong, W. M., Wong, W. K., Lean, H. H., 2005. International momentum strategies: A stochastic dominance approach. Journal of Financial Markets. 8, 89-109.

Gasbarro, D., Wong, W. K., Zumwalt, J. K., 2007. Stochastic dominance analysis of iShares. European Journal of Finance. 13, 89-101.

Hanoch, G., Levy, H., 1969. The efficiency analysis of choices involving risk. Review of Economic Studies. 36, 335-346.

Hadar, J., Russell, W. R., 1969. Rules for ordering uncertain prospects. American Economic Review. 59, 24-34.

Hull, J. and White, A., 1987, The pricing of options on assets with stochastic volatilities. The Journal of Finance, 42, 281-300.

Horst, J. t., Veld, C., 2008. An Empirical Analysis of the Pricing of Bank Issued Options versus Options Exchange Options. European Financial Management. 14, 288-314

Isakov, D., Morard, B., 2001. Improving portfolio performance with option strategies: Evidence from Switzerland. European Financial Management. 7, 73-91.

Jarrow, R., 1986. The relationship between arbitrage and first order stochastic dominance. Journal of Finance. 41, 915-921.

Kaur, A., Rao, B. L. S. P., Singh, H., 1994. Testing for second-order dominance of two distributions. Econometric Theory. 10, 849-866.

Kou, S. G., 1999, A jump diffusion model for option pricing with three properties: leptokurtic feature, volatility smile, and analytical tractability. Working paper. Columbia University, New York.

Lamoureux, C. G., Lastrapes, W. D., 1993. Forecasting stock-return variance: toward an understanding of stochastic implied volatilities. Review of Financial Studies. 6, 293-326.

Latane, H. A., Rendleman, R, J., 1976. Standard Deviations of Stock Price Ratios Implied in Option Prices. The Journal of Finance. 31, 369-381.

Lean, H. H., Wong, W. K., X. B. Zhang., 2008. Size and power of some stochastic dominance tests. Journal of Statistical Computation and Simulation. 79, 30-48.

Lean, H. H., McAleer, M., Wong, W. K., 2010. Market efficiency of oil spot and futures: A mean-variance and stochastic dominance approach, Energy Economics, Forthcoming.

Leshno, M., Levy, H., 2002. Preferred by “All” and preferred by “Most” decision makers: Almost stochastic dominance. Management Science. 48, 1074-1085.

Linton, O., Maasoumi, E., Whang, Y. J., 2005. Consistent testing for stochastic dominance under general sampling schemes. Review of Economic Studies. 72, 735-765.

Machina, M. J., 1982. Expected utility analysis without the independence axiom. Econometrica. 50, 277-323.

Manaster, S., Rendleman, J., 1982. Option prices as predictors of equilibrium stock prices. Journal of Finance. 37, 1043- 1057.

McFadden, D., 1989. Testing for stochastic dominance, in: Formby. Springer Verlag, New York.

Petrella, G. 2006. Option Bid-Ask Spread and Scalping Risk: Evidence from a covered warrants market. Journal of Futures Markets. 26, 843-867.

Porter, R. B., 1973. An empirical comparison of stochastic dominance and mean-variance portfolio choice criteria. Journal of Financial and Quantitative Analysis. 8, 587-608.

Porter, R. B. and Gaumnitz, J. E., 1972. Stochastic dominance vs. mean-variance portfolio analysis: An empirical evaluation. American Economic Review. 62, 438-446.

Quirk, J.P., Saposnik, R., 1962. Admissibility and measurable utility functions. Review of Economic Studies. 29, 140-146.

Richmond, J., 1982. A general method for constructing simultaneous confidence intervals. Journal of the American Statistical Association. 77, 455-460.

Roll, R., 1977. An analytic valuation formula for unprotected American call options on stocks with known dividends. Journal of Financial Economics. 5, 251-258.

Rothschild, M., Stiglitz, J.E. 1970. Increasing Risk I. A Definition. Journal of Economic Theory. 2, 225-243.

Rothschild, M. and Stiglitz, J., 1976. Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information. The Quarterly Journal of Economics. 90, 629-649.

Russell, W. R., Seo, T. K., 1978. Ordering Uncertain Prospects: The Multivariate Utility Functions Case. The Review of Economic Studies. 45, 605-610.

Russell, W.R., Seo, T.K., 1989. Representative sets for stochastic dominance rules. In: Fomby. Springer, New York.

Stein, J., 1987. Information externalities and welfare-reduction speculation. Journal of Political Economy. 95, 1987, 1123-1145.

Starmer, C., 2000. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. Journal of Economic Literature. 38, 332-82.

Stoline, M.R., Ury, H.K., 1979. Tables of the studentized maximum modulus distribution and an application to multiple comparisons among means. Technometrics. 21, 87-93.

Taylor, S., 1994. Modelling stochastic volatility. Mathematical Finance. 4, 183-204.

Tse, Y. K., Zhang, X., 2004. A Monte Carlo investigation of some tests for stochastic dominance. Journal of Statistical Computation and Simulation. 74, 361-378.

Von Neumann, J., Morgenstern, O., 1944. Theory of Games and Economic Behavior. Princeton University Press, Princeton, NJ.

Whalley, E., 2008. Reservation bid and ask prices for options and covered warrants: portfolio effects. Working paper.

Whitmore G.A., 1970. Third-degree Stochastic Dominance. American Economic Reivew. 60, 457-459.

Wong, W. K., Chan, R., 2008. Markowitz and prospect stochastic dominances. Annals of Finance. 4, 105-129.

Wong, W.K., Ma, C. 2008. Preferences over Meyer's Location-Scale Family. Economic Theory. 37, 119-146.

Wong, W. K., Phoon, K. F., Lean, H. H., 2008. Stochastic dominance analysis of Asian hedge funds. Pacific-Basin Finance Journal. 16, 204-223.

Xu, K., 1997. Asymptotically distribution-free statistical test for generalized Lorenz curves: An alternative approach. Journal of Income Distribution. 7, 45-62.

Xu, X., Taylor, S. J., 1995. Conditional volatility and information efficiency of the PHXL currency options market. Journal of Banking and Finance. 19, 803-21.

Footnotes

1 Covered warrants, however, normally contain a "covered agreement," which stipulates the amount of the underlying asset to be held by the issuer to cover (hedge) the position.

2 The presence of abnormal returns estimated from such models indicates market inefficiency on the one hand, as opposed to misestimated factors, omitted factors or model misspecification on the other.

3 Diltz and Kim (1996) excluded 10 days of trading statistics prior to the option expiration; however, as covered warrants have longer periods to maturity as compared with options, we increased this period of exclusion to 15 days.

4. Implied standard deviations have been investigated by Latané and Rendleman (1976), and Chiras and Manaster (1978).

5. The SD test developed by Linton et al. (LMW, 2005) is also a highly regarded test. In this paper, we also apply the LMW test to analyze the data for robustness. As the conclusion drawn from the LMW SD test is the same as that drawn from the DD test, we do not report on the results of the LMW test in this paper.

6. For convenience, we redefine the CDFs of W and S to be F_W and F_S, respectively, as opposed to the F and G we used in the previous sections.

7. Refer to Lean et al. (2007) for the reasoning. Critical values are 3.691, 3.254 and 3.043 for the 1%, 5% and 10% levels of significance, respectively, as tabulated in Stoline and Ury (1979).

8. We note that Leshno and Levy (2002) use an example of 1% to state the problem of almost SD. In this paper, we follow Fong et al. (2005) and Gasbarro et al. (2007) to choose a more conservative 5% cut-off point to avoid the problem of almost-SD.

9. The empirical evidence decisively demonstrates a rejection of the hypothesis that the distribution of a return Rt, conditional upon the information set It-1 of past returns, is normal for high-frequency data (Engle and Bollerslev, 1986; Baillie and Bollerslev, 1989; Taylor, 1994). Two empirically better conditional distributions are the scaled t and the generalized error distribution (GED) (Taylor, 1994).

10. Claessen and Mittnik (2002) suggest that the maturity mismatch of the GARCH and the IV forecasts might be problematic. The GARCH model predicts the conditional variance for the next period (here, the next day), and the IV variable represents market expectations for the average daily volatility over the remaining lifetime of the covered warrant. But Xu and Taylor (1995) found no evidence suggesting that the choice of the IV predictor affects the predictive power of the mixed GARCH-IV model.

11.In the GED distribution, γ is the tail parameter, which is always positive. The GED is a Gaussian distribution when γ =2, and fat-tailed if r is lower than 2. We estimated γ for each pair and imposed the estimated r in the LR test.

12.We note that we also apply the approach recommended by Bai et al. (2009) to use simulated critical values and maximum values for the DD test. As our conclusions match those of Bai et al. (2009), we do not discuss their approach or the corresponding results.

13. In total, three $T^j(x_i)$ out of 100 are higher than 3.254.Thus we do not reject the null hypothesis for this case.