OPTION TRADE VOLUME AND VOLATILITY OF BANKS' STOCK RETURNS*

*Rafael Barbosa*** | *Martín Saldías***

ABSTRACT

This article focuses on the linkages between the trading activity in option markets and the volatility of their corresponding underlying stocks. More specifically, we try to answer the question of whether the trading volume in the option markets has explanatory power over the volatility of the underlying stocks. We focus on option and stock prices information from 16 large European and US banks between 2004 and 2008. Our results show that option trading volume has explanatory power over returns' volatility and it is robust after controlling for increased overall volatility and shifts in the volatility regime in the early stages of the crisis. The analysis of this particular linkage is scarce in the existing literature and almost non-existent for the European banking sector.

1. Introduction

The analysis of volatility of stock returns draws a lot of attention in the financial economics literature. In the case of banks' stocks, this is also related to its connection to overall market instability. Although volatility does not necessarily imply financial instability and it is common to come across periods of price turmoil without any reflection in liquidity or solvency concerns, it is also very rare to witness the latter without the former. In a sense, volatility seems to be a necessary ingredient in the recipe for market instability. It is therefore very relevant to identify and analyze the determinants of equity returns' volatility to understand and assess financial instability.

One of the most consensual of these determinants of volatility in the literature is stock trading volume. Several papers have demonstrated that there is a positive relationship between the two. However, due to its growing relevance in the last decades recent work has started to study whether derivative markets in general and equity option markets in particular may contain relevant information about stock volatility. Moreover, in recent times, large institutional market players have been showing an increasing interest towards options as a risk mitigating strategy. This can represent an inflow of highly informed market players that contribute to deepen the informational potential of this market in relation to the underlying market.

Along these lines, this article explores the relationship of trading activity in options of banks and the volatility of their corresponding underlying stocks. In particular, we focus on the role of trading volume in regulated option markets as an explanatory variable of the volatility of the underlying stocks. We focus on option and stock prices information from 16 large European and US banks between 2004 and 2008 and conduct an analysis based on extended EGARCH models.

Our results show that the contemporaneous trading volume in the options market helps explain the

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** Banco de Portugal, Economic Research Department.

volatility of the underlying stock for a representative sample of some of the largest banks in Europe and the US. Furthermore, this relationship does not seem to be affected by periods of increased market volatility like the subprime crisis. This research can thus be a valuable contribution to the analysis of banks' stocks volatility and help assess market instability.

Usually, the search for information about volatility in option markets is focused on the study of implied volatilities. Christensen and Prabhala (1997) claim that implied volatility outperforms past volatility in forecasting future volatility and even subsumes the information content of past volatility in some specifications. However, the previously mentioned link between stock volume and stock volatility begs the question of whether the trading activity in the option market may also contain relevant information about this subject.

The first paper to study this relation directly was Park, Switzer and Bedrosian (1999), motivated by similar work concerning the linkages between stock return volatility and trading volume in futures market, namely Bessembinder and Seguin (1992). The authors find that the unexpected trading activity in option markets indeed holds strong explanatory power over the volatility of the underlying stock returns, while expected volume only impacts a minority of firms and with lesser magnitude. More recently, Ni, Pan, and Poteshman (2008) find that a non-market maker net demand for volatility constructed from the trading volume of individual equity options is informative about the future realized volatility of underlying stocks (with a positive impact).

Ho, Zheng and Zhang (2012) provide the motivation of this article. In their work, a sample of the 15 stocks with highest option trade volume in the New York Stock Exchange from 2002 until 2006 is analyzed. Their findings are consistent with the theory that a higher level of trading activity in the option market leads to a higher degree of volatility in the underlying stock.

Intuitive reasons to explain this phenomenon are put forward in the paper by Ni, Pan and Poteshman (2008), claiming that investors choose to trade on private information about volatility in the option market. This happens to a large extent because option markets allow investors to perform option spreads and combinations, some of which are prime instrument for when investors have information about the magnitude of future volatility but not on the future direction of returns of the stock. This is consistent with another finding of the paper, in which the predictive power of option volume increases in the days leading up to earning announcements by the firms, when information asymmetry also reaches its peak.

These combinations allow investors to create strategies which can be delta neutral, *i.e.* not sensitive to directional changes in the underlying, but are instead very dependent on its volatility.

Although there are many possible combinations for option trading strategies, a number of them are most popular among investors. Chaput and Ederington (2002) tackled this issue and also assessed whether trading volume is relevant relative to the total number of trades in the market. Their results point out first to the fact that combination trades account for 55% of total trades and 75% of trading volume. Second, the most heavily traded of all combinations are straddles, ratio spreads, vertical spreads, and strangles[1]. These figures leave an open window concerning the possibility that informed traders are using these combinations to capitalize on the future volatility of the underlying stocks.

In this article, the methodology used to study the impact of option volume on return volatility will be based on Ho *et al.* (2012), in which an EGARCH approach is used to model the conditional heteroskedasticity of the returns, using as explanatory variables of interest two ratios that according to the authors, provide a valuable approach because it allows us to evaluate market sentiment in comparison with the past.

1 A Straddle is constructed by buying a call and a put, both with same exercise price and same time to maturity. A Strangle is similar to a straddle, but the call has an exercise price higher than the put. Call (Puts) Ratio spreads consist of buying X calls (puts) and sell Y calls (puts) with a different strike and with X>Y. Vertical spreads are directional spreads, and therefore are not of interest for the subject of this paper.

The data set used consists of daily option information on several large banks and spans from January 2nd 2004 to December 31st 2008.[2] As such, the last period includes the onset of the Subprime financial crisis, an element of interest in our analysis and that will allow us to study whether the potential informative content of option volume on stock volatility may have changed during a period of market instability. Additionally, some of the banks in our sample underwent singular circumstances, such as recapitalizations and mergers.

Our analysis focuses on banks because they are consistently a preferred choice of investors in option markets, which can strengthen the link between this type of derivatives and the underlying stock.[3] Moreover, the diversity in the size of the banks under analysis can actually be a plus in the sense that it allows us to determine whether there is evidence that the potential explanatory power of option trading activity over volatility holds even for companies with a more modest volume of traded options. Swidler and Wilcox (2002), similarly to Christensen and Prabhala (1997), have shown that equity options on banks, through implied volatilities, forecast the volatility of the underlying stock. Therefore, it is relevant to study the role of trading volume in this dynamic.

We find evidence that the option volume variables that we include have a positive effect on the conditional volatility, even after controlling for the notoriously high volatility that took over the financial markets in late 2007. Stock volume also exerts the same type of influence.

The rest of the paper is structured as follows. Section 2 describes the methodology. Section 3 describes the data and discusses particular cases of interest concerning the analysis. Section 4 presents the results. Finally, section 5 concludes.

2. Methodology

As it is common in the literature, volatility models of financial market returns often incorporate conditional heteroskedasticity from the family of GARCH models. Accordingly, the baseline model in this paper is an EGARCH model (Christie, 1982 and Nelson, 1991) that accounts for conditional heteroskedasticity and also captures asymmetry in volatility clustering.

Asymmetric volatility is a frequent phenomenon observed in financial data and refers to the fact that large positive deviations from the mean do not have the same impact on volatility as negative shocks. In fact, downward moves are usually associated to a greater effect on volatility, a characteristic that standard ARCH and GARCH models are unable to capture.

In order to model this additional feature of stock returns, usually referred to as leverage effects, Nelson (1991) proposed the Exponential GARCH (EGARCH) which does not impose any non-negativity restriction on the parameters. Assuming a Gaussian innovation distribution, the baseline model assumes the following form for the variance equation:

$$\log\left(h_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log\left(h_{t-1}\right) \tag{1}$$

where β_1 is the ARCH term, β_2 the GARCH, while the γ parameter captures the leverage effect. If the latter is significant and negative, there is statistical evidence of asymmetry in stock return volatility, and thus that negative shocks are more prone to increase volatility than positive shocks.

In order to study the impact of option trading volume upon volatility we will use two measures put forward by Ho *et al.* (2012), called RCALL and RPUT ratios. They aim to capture the intensity of trading

2 June 30th 2009 for three Banks. See Table 1 for details.

3 Despite this fact, this does not mean that all banks in the sample have especially large option trading activity. We chose, however, the banks with largest trading volumes over the time span.

activity relatively to the last 60 trading days[4] and are defined as follows:

$$RCALL60_t = \frac{Call\,Trading\,Volume\,at\,time\,t}{Mean\,of\,Call\,Volume\,in\,the\,past\,60\,days} \tag{2}$$

$$RPUT60_t = \frac{Put\,Trading\,Volume\,at\,time\,t}{Mean\,of\,Put\,Volume\,in\,the\,past\,60\,days} \tag{3}$$

The final version of the model, as in Ho *et al.* (2012), combines the baseline model (1) with the log of the two option ratios and the log of stock volume (SVOL) in the variance equation. The mean equation associated with the variance equation in that paper is an ARMA (p,q) model.

For the sake of simplicity, we will, by default, perform the regressions including only a constant in the mean equation. Additionally, we will also use log difference instead of standard logs in our regressions. This is what the model looks like after these adjustments:

$$\log\left(h_t\right) = \omega + \beta_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + \gamma\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2\log\left(h_{t-1}\right) + \beta_3\mathrm{dlog}\left(RCALL60_t\right) + \beta_4\mathrm{dlog}\left(RPUT60_t\right) + \beta_5\mathrm{dlog}\left(SVOL_t\right) \tag{4}$$

In our analysis it will also be extremely important to account for overall market volatility, specifically since the onset of the financial crisis. This phenomenon was a driver of alarm and soaring volatility in the returns of nearly all financial instruments across the globe. Merely observing the volatility charts for the banks at our disposal (Chart 1), it is clear that there are permanent shifts in the pattern of volatility. It would be unwise to model the volatility of the stocks in our sample without having this into account. The reasons are addressed, for instance, in Hamilton (1994), where the author warns about the risk that changes in volatility regime can create distortions, such as the illusion of long term persistence in the estimates of the terms regarding conditional heteroskedasticity. He draws a parallel between this phenomenon and the demonstration of Perron (1989), in which he proves that changes in regimes can give the spurious impression of unit roots in the level of a series.

In order to address this issue, we conduct structural break tests on the return volatility of the banks in our sample. These tests are based on the methodology devised by Kokoszka and Leipus (2000) and used, for instance in Rodrigues and Rubia (2011), which is an improvement over the cumulative sums of squares tests (CUSUM) applied to ARCH models proposed in Inclán and Tiao (1994), in the sense that it allows for the relaxation of the assumption that the variable under analysis must be iid The most attractive aspect of these tests is that it endogenously infers the most likely break positions.

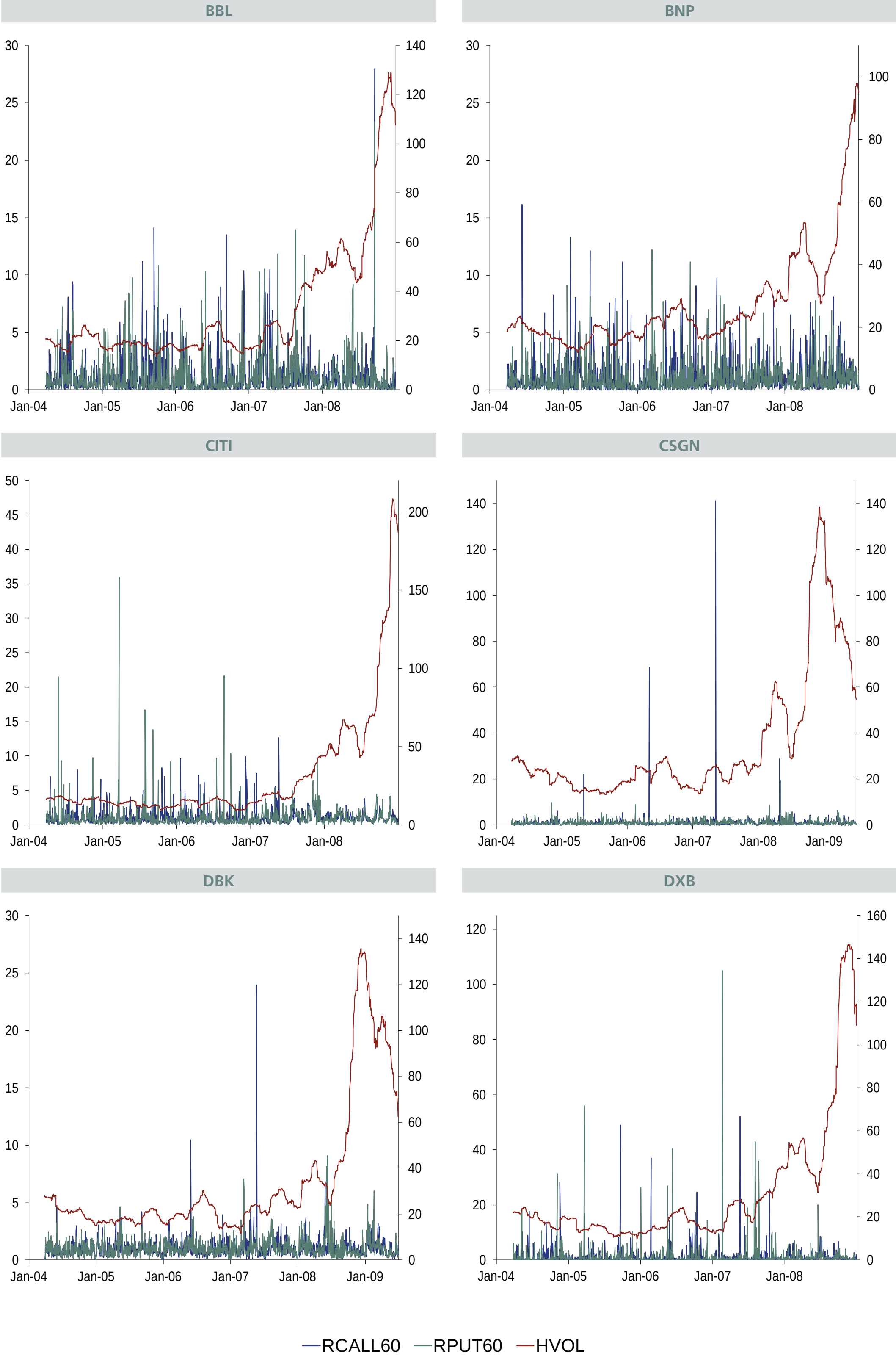
The results of the break tests are consistent. The vast majority of banks present two breaks: the first takes place around July 2007, while the second takes place more than one year after that, in October 2008. These periods are coincidental with two major events in the subprime crises: the first with the emergence of financial problems in Northern Rock that would later have to be nationalized; the second with the bankruptcy of Lehman Brothers. The difference in estimates of the dates between banks for both breaks is not greater than two weeks. Both the 2007 and the 2008 breaks translate into upward volatility jumps.

In order to model this abnormality in the volatility of returns we decided to include dummy variables to distinguish the three regimes. The first is a low volatility regime that lasts until June 2007. The second is characterized by a medium volatility regime and comprises the period from the beginning of July 2007 until the end of September 2008. Finally, the last regime, starting in October 2008, can only be described as a volatility whirlwind. We expect that if any relation exists it survives the inclusion of these new control variables.

4 Other time horizons were also used to test for robustness, namely 30 and 90 days. These robustness tests showed similar results and are not reported.

Chart 1 (continue)

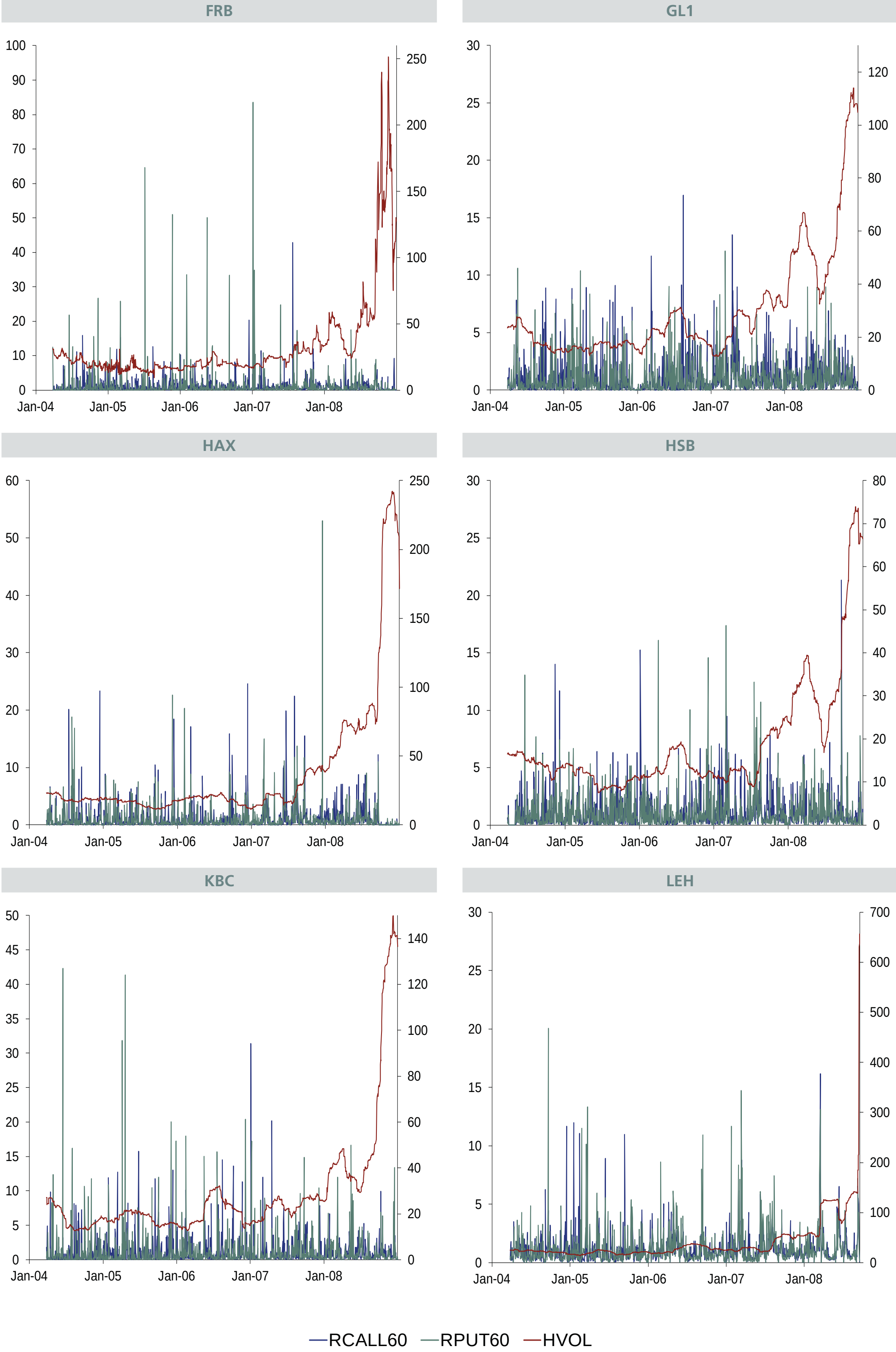
GRAPHS OF HISTORICAL VOLATILITIES (HVOL), RCALL60 AND RPUT60 (LHS)



Sources: Bloomberg, Eurex, CBOE, Euronext and authors' calculations.

Chart 1 (continuation)

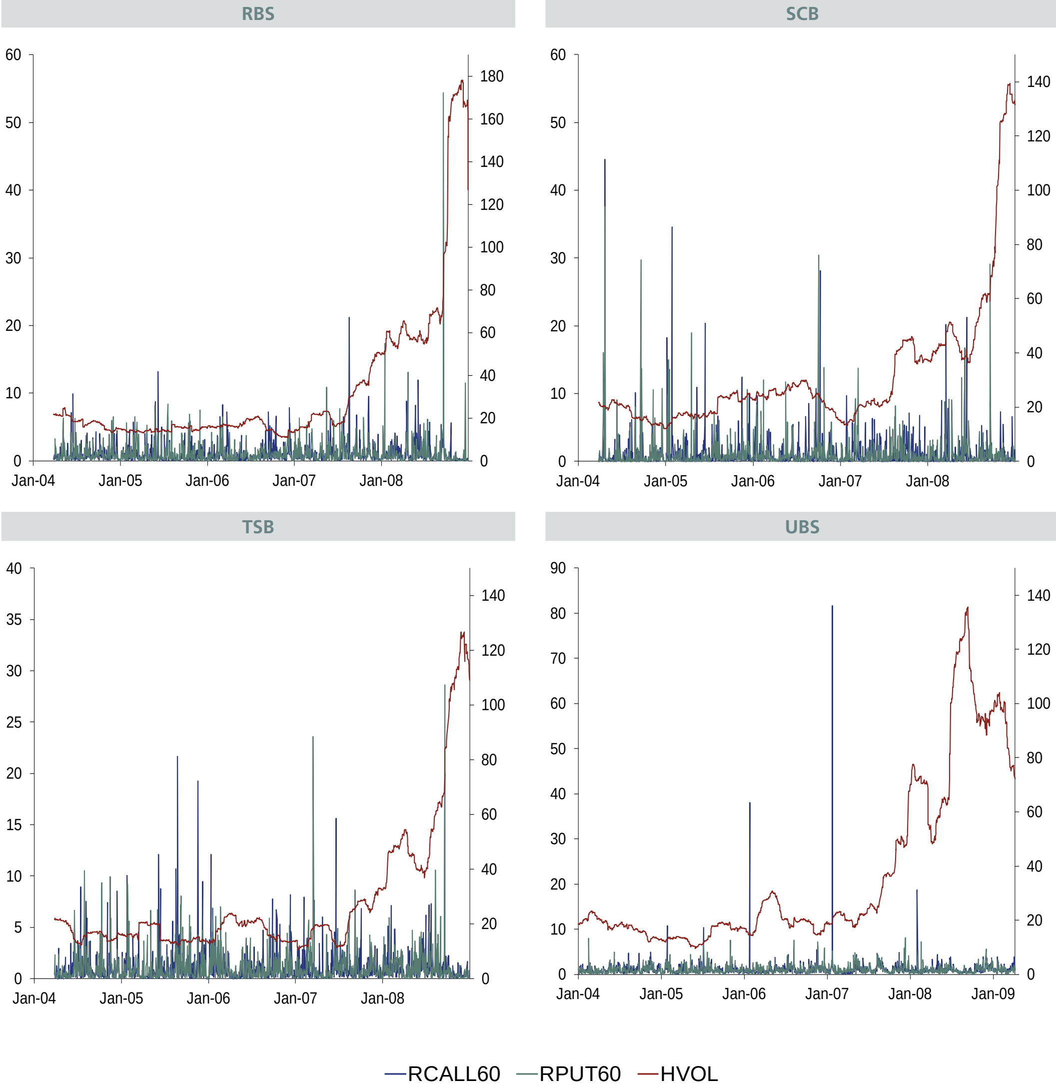
GRAPHS OF HISTORICAL VOLATILITIES (HVOL), RCALL60 AND RPUT60 (LHS)



Sources: Bloomberg, CBOE, Eurex, Euronext and authors' calculations.

Chart 1 (continuation)

GRAPHS OF HISTORICAL VOLATILITIES (HVOL), RCALL60 AND RPUT60 (LHS)



Sources: Bloomberg, CBOE, Eurex, Euronext and authors' calculations.

Taking into consideration that the dates for the breaks present a considerable consistency (with differences for the estimates of different banks not surpassing two weeks) and for the sake of simplification, we decided to impose the same date for all banks. In the case of the first structural break the selected date was July 1st 2007 and for the second, October 1st 2008. It is important to mention that the first dummy assumes the value of 1 on July 2007, and then remains at this level until the end of the sample period. This implies that the coefficient on the final dummy (starting in October 2008) will capture the potential incremental increase in unconditional volatility in relation to the period immediately preceding it, *i.e.,* the medium volatility regime, and not the initial one. This will allow us to compare directly whether there was a greater increase in unconditional volatility from the first regime to the second or from the second to the third. With this addition, the model presented in (4) becomes:

$$\log(h_t) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log(h_{t-1}) + \beta_3 \text{dlog}(RCALL60_t) + \beta_4 \text{dlog}(RPUT60_t) + \beta_5 \text{dlog}(SVOL_t) + \beta_6 SUBP_t + \beta_7 SUBP2_t \tag{5}$$

Alternatively, we also stressed the robustness of our model by including a market volatility variable instead of the dummies. We measured market volatility (MVOL) using the VIX volatility Index for American and British banks and the VSTOXX Volatility Index for all other European Banks to control for any variation in the volatility of stock returns that was due to overall instability in the market, rather than to bank specific drivers. This specification is presented below.

$$\log\left(h_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log\left(h_{t-1}\right) + \beta_3 \mathrm{dlog}\left(RCALL60_t\right) + \beta_4 \mathrm{dlog}\left(RPUT60_t\right) + \beta_5 \mathrm{dlog}\left(SVOL_t\right) + \beta_6 MVOL_t \quad (6)$$

For reasons presented in Section 1 and based on the findings of Ho *et al.* (2012) and Poteshman *et al.* (2008), we expect to find that, throughout these models, both the stock and option trading volume variables are significant and that they positively affect the volatility of the underlying stock.

3. Data

The dataset comprises daily stock and option prices of 16 large banks between January 2004 and December 2008 (June 2009 for three banks). Stock prices are retrieved from Bloomberg, while option information to compute the RCALL and RPUT ratios come from three sources, namely CBOE, Euronext and Eurex. These option databases are very rich, containing information for all listed option contract maturities and strike prices on any given day. Therefore, in order to acquire a figure for total traded options in one day, we had to aggregate the volume of every contract that was traded during that day. The list of stocks included in our sample, corresponding code, data source and data availability is available in Table 1.

Besides diversity, our sample stands out due to the size and systemic importance of several of the banks included. In Table 2 we can see a list of the banks with highest systemic risk in Europe in 2012 as presented in Engle, Jondeau, and Rockinger (2012). Out of the top 10 banks indentified, eight of them are part of our sample.[5] These are naturally also the banks with largest asset size and which draw most attention in the financial markets. This can be seen by glancing through the figures for average stock trading volume in Table 2, which shows that the shares of most of these banks are traded millions of times per day.

Tables 3 and 4 present some important descriptive statistics for each bank throughout the period under analysis. Table 3 shows the mean and standard deviation of daily total traded volume of calls (TVOLC) and puts (TVOLP), as well as open interest (TOIC and TOIP) and number of shares traded (SVOL). We can see that the sample is very diverse, ranging from the less traded Belgian banks like Fortis or KBC, with average option trading volume ranking in the hundreds, to tens of thousands of traded options on average every day in the case of Deutsche Bank or Lloyds Banking Group. The difference is equally striking in what concerns the underlying stock, although obviously at a much larger scale, with the most heavily traded stocks being traded several dozen million times per day.

It is also worthwhile to point out that for most of the sample, call trading volume is larger than put trading volume, a finding consistent with Poteshman *et al.* (2008) and Ho *et al.* (2012). This feature is likely to be a consequence of the fact that many investors, especially the most novice, have a tendency to favor being on the long side of the market. Another theory is that short-term traders prefer to trade in-the-money calls since they have higher delta and gamma and can therefore provide faster profits.

In Table 4 we can see information on option contracts for each firm, more specifically average and standard deviation of the total number of contracts listed (TOT), of number of contracts that are actively traded (POSV) and of those with positive open interest (POSOI), as well as a measure of relative traded contracts (RV) which is the ratio of POSV and TOT, *i.e.* the number of traded contracts as a percentage of listed contracts. All these measures are presented for calls and puts separately. In this regard, there is still some disparity in the number of contracts listed and traded between both types of options, in

5 Deutsche Banke, Barclays, BNP Paribas, RBS, Société Générale, HSBC, Lloyds and UBS.

Table 1

DESCRIPTION OF BANKS UNDER ANALYSIS			
Code	**Bank**	**Country**	**Source**
BLL	*Barclays*	UK	*Euronext*
BNP	*BNP Paribas*	France	*Euronext*
CITI	*Ctitigroup*	USA	*CBOE*
CSGN	*Credit Suisse*	Switzerland	*Eurex*
DBK	*Deutsche Bank*	Germany	*Eurex*
DXB	*Dexia*	Belgium	*Euronext*
FRB	*Fortis*	Belgium	*Euronext*
GL1	*Société Générale*	France	*Euronext*
HAX	*Halifax/HBOS*	UK	*Euronext*
HSBC	*HSBC*	UK	*Euronext*
KBC	*KBC*	Belgium	*Euronext*
LEH	*Lehman Brothers*	USA	*CBOE*
RBS	*Royal Bank of Scotland*	UK	*Euronext*
SCB	*Standard Chartered Bank*	UK	*Euronext*
TSB	*Lloyds Banking Group*	UK	*Euronext*
UBS	*UBS*	Switzerland	*Eurex*

Source: Banco de Portugal.

Note: The data on options comes from three sources: First, the NYSE LIFFE NextHistory Equity Derivatives EOD which contains daily data on option contracts traded on Liffe for Amsterdam, Brussels, Lisbon, London and Paris. Second, the Eurex, which includes information on the German and Swiss Banks studied and, finally, the CBOE from where data on the American Banks was gathered. The variables available included in the database and that were used are type of contract (Put or Call), exercise price, price of underlying stock and trading volume. Data is available for all firms from 01/01/2004 until 31/12/2008, except CSGN, DBK and UBS, for which data is available until 30/06/2009 and LEH, for which data is available until 17/09/2008.

Table 2

RANKING OF EUROPEAN FINANCIAL INSTITUTIONS ACCORDING TO SYSTEMIC RISK					
Ranking	**Institution**	**Country**	**SRISK (mM €)**	**Leverage**	**Mkt. Cap. (mM €)**
1	Deutsche Bank	Germany	162	84.8	26.1
2	Barclays	UK	141.9	69.4	28.3
3	Credit Agricole	France	134.5	151.6	11.6
4	BNP Paribas	France	131	44.3	43.3
5	RBS	UK	126.2	96.8	17.6
6	Societe Generale	France	88.7	73.6	16.4
7	ING Group	Netherlands	86.4	51.7	23.3
8	HSBC	UK	76.5	16.5	126.2
9	Lloyds Banking	UK	73.2	39.1	29.5
10	UBS	Switzerland	72.7	34	34.1

Sources: Engle, R., Jondeau, E. and Rockinger, M. (2012), "Systemic Risk in Europe", (December 1, 2012), *Swiss Finance Institute Research Paper No. 12-45*.

Note: This table, found in Engle, Jondeau, and Rockinger (2012), reports the ranking of European financial firms by SRISK (a measure of systemic risk) as of 30th August 2012. For each firm, we report the name, country, SRISK (in billion euros), leverage, and market capitalization (in billion euros).

Table 3

OPTION AND STOCK VOLUME STATISTICS

		TvolC	TVolP	TOIC	TOIP	SVOL
	MEAN	720	599	57 456	63 990	50 232 250
BLL	ST DEV	1 407	1 218	54 021	61 891	36 189 067
	MEAN	3 774	3 371	153 943	185 390	4 692 472
BNP	ST DEV	7 255	6 496	135 967	196 232	2 687 544
	MEAN	14 645	11 852	1 228 046	1 130 797	4 315 337
CITI	ST DEV	19 651	19 274	876 549	790 445	6 721 819
	MEAN	10 954	9 895	539 860	575 602	7 501 691
CSGN	ST DEV	36 557	15 513	189 686	163 158	4 550 479
	MEAN	17 922	19 785	828 724	896 227	6 343 930
DBK	ST DEV	15 823	21 350	201 257	185 812	4 227 158
	MEAN	213	148	8 763	8 397	2 813 596
DXB	ST DEV	561	409	3 594	2 884	2 868 950
	MEAN	76	56	3 249	2 431	10 349 337
FRB	ST DEV	148	161	1 421	1 305	12 991 144
	MEAN	3 416	2 547	128 948	132 994	3 313 260
GL1	ST DEV	6 975	5 059	113 740	134 334	2 879 435
	MEAN	231	287	16 885	18 861	26 980 858
HAX	ST DEV	619	821	21 640	21 081	32 959 915
	MEAN	900	784	112 281	116 874	50 883 210
HSB	ST DEV	1 398	1 192	65 787	69 026	25 565 666
	MEAN	131	115	5 851	4 571	706 306
KBC	ST DEV	292	281	3 275	2 807	434 287
	MEAN	4 583	6 349	213 705	268 524	12 416 269
LEH	ST DEV	12 564	16 460	216 362	275 169	30 963 942
	MEAN	538	504	53 141	54 407	5 260 241
RBS	ST DEV	1 869	1 991	79 578	77 528	3 374 273
	MEAN	67	64	3 521	4 345	9 279 104
SCB	ST DEV	134	130	1 843	3 335	6 603 881
	MEAN	649	508	40 732	41 874	85 744 720
TSB	ST DEV	1 149	1 039	17 647	19 581	61 956 876
	MEAN	12 991	12 596	582 554	505 334	13 712 210
UBS	ST DEV	33 661	22 094	361 177	271 337	11 828 664

Sources: Bloomberg, CBOE, Eurex and Euronext.

Note: TVolC (TVolP) is the total number of Calls (Puts) traded per day; TOIC (TOIP) is the Open Interest of Calls (Puts) per day; SVOL is the total number of stocks traded per day.

line with what we observed in terms of trading volume. The smaller number of average listed contracts is around 50, while on the opposite end we have the largest banks with about 250 contracts available per day. However, the value for relative traded contracts (RV) is much more homogeneous, with most banks presenting figures around the 10% mark. The only exceptions to this seem to be the American banks (Lehman and Citigroup), possibly evidencing a greater dynamism in the US options market and also more heterogeneous beliefs amongst investors. We can also see that the value for RV is usually very similar for calls and puts of a given bank.

Chart 1 depicts the historical volatility of all the stocks in our sample as well as the option ratios used in our analysis, presented in equations (2) and (3). We can easily observe the increased volatility in the final months of the observation period across all banks in our sample, as we would have expected. It is worthwhile to observe that the rolling window in RCALL and RPUT prevents the appearance of sustained drifts in these variables.

Table 4

OPTION CONTRACTS STATISTICS									
		CALLS				PUTS			
		TOT	POSV	POSOI	R	TOT	POSV	POSOI	R
BLL	MEAN	136.4	10.2	78.5	9%	136.4	12.5	83.6	11%
	ST DEV	42.2	4.5	23.0	5%	42.2	5.5	21.8	5%
BNP	MEAN	128.3	7.9	48.1	6%	128.3	8.6	57.0	7%
	ST DEV	25.4	6.2	25.3	4%	25.4	6.0	24.6	4%
CITI	MEAN	99.5	56.5	92.3	57%	99.5	49.1	92.1	49%
	ST DEV	9.7	17.1	19.5	16%	9.7	15.5	19.4	15%
CSGN	MEAN	258.7	30.1	164.4	12%	258.6	32.7	182.9	13%
	ST DEV	82.8	16.4	64.1	5%	82.8	16.9	57.8	6%
DBK	MEAN	249.4	44.9	169.5	18%	249.4	48.1	178.4	20%
	ST DEV	96.2	21.2	74.0	6%	96.2	23.2	66.1	6%
DXB	MEAN	55.6	4.0	35.0	7%	55.6	2.8	34.0	5%
	ST DEV	23.3	4.3	17.3	6%	23.3	3.6	15.4	5%
FRB	MEAN	64.5	3.0	36.7	5%	64.5	1.7	30.2	3%
	ST DEV	39.5	3.0	21.5	4%	39.5	2.2	10.9	4%
GL1	MEAN	148.0	7.6	54.2	5%	148.0	7.9	61.3	6%
	ST DEV	73.8	6.5	30.3	4%	73.8	5.6	24.3	4%
HAX	MEAN	72.07	4.65	36.28	10%	72.07	5.64	39.03	12%
	ST DEV	83.20	4.24	33.27	9%	83.20	5.51	31.86	9%
HSB	MEAN	99.5	7.1	52.9	7%	99.5	7.8	55.8	8%
	ST DEV	15.4	4.4	19.6	4%	15.4	5.3	20.3	5%
KBC	MEAN	52.8	4.5	31.2	8%	52.8	3.9	33.3	7%
	ST DEV	14.7	3.9	13.1	7%	14.7	4.4	12.7	7%
LEH	MEAN	93.0	25.1	82.8	25%	93.0	22.7	78.9	22%
	ST DEV	25.2	21.0	30.8	14%	25.2	21.5	30.2	14%
RBS	MEAN	127.1	9.3	59.7	8%	127.1	10.7	65.3	9%
	ST DEV	62.1	6.0	33.7	4%	62.1	7.2	27.2	5%
SCB	MEAN	34.4	3.3	22.5	10%	34.4	3.5	23.5	10%
	ST DEV	15.5	2.8	8.1	8%	15.5	2.7	8.2	8%
TSB	MEAN	96.6	8.2	48.9	8%	96.6	9.1	58.8	9%
	ST DEV	34.3	5.2	25.1	5%	34.3	6.2	22.2	5%
UBS	MEAN	239.6	32.5	157.9	14%	239.6	36.0	172.2	15%
	ST DEV	98.8	18.9	88.6	6%	98.8	22.3	77.4	7%

Sources: CBOE, Eurex, Euronext and authors' calculations.

Note: TOT is the total number of option contract types for a specific bank per day; POSV is the number of contracts that presented positive trading volume in a day; POSOI is the number of option contracts that presented positive open interest in a day. R is the ratio between POSV and TOT, that is, the contracts with positive trading volume as a percentage of all available contracts.

For this reason, observing the absolute volume of traded options may also be relevant to understand the dynamics of this market during the period under analysis. In Chart 2 we present the 12-month moving average of this variable for calls and puts of all banks in the sample. Although there is some heterogeneity across banks, the most usual pattern is an upward trend in traded volume of all options starting roughly in early 2007 and which lasts until the third quarter of 2008. At this point, there seems to be stabilization and in some cases even an inversion of this trend, arguably caused by the sharp fall in liquidity following the bankruptcy of Lehman Brothers. During the peak of trading activity we can also detect that for most banks put volume surpasses call volume, in contrast to what we observe for most of the sample period, which can be interpreted as market perception of future generalized decline in stock prices.

Before moving to the estimation results, it is also important to mention peculiarities in some of the banks in our sample during the period under analysis. First and foremost there is the case of Lehman Brothers, which, as is known, went bankrupt on October 15th 2008, thus being the bank with the least amount of time in our sample as well as deserving special treatment concerning the year before bankruptcy throughout which Lehman incurred in constant and heavy losses. Secondly, Citigroup received $25 billion of financial help in the form of TARP (Troubled Asset Relief Program) Federal funds in November 2008. Last of all, there is the case of the Royal Bank of Scotland (RBS) which benefited from a recapitalization with government money in October 2008.

4. Model Estimation

4.1. EGARCH (1,1)

Estimation results from the benchmark model defined in equation (1) are presented in Table 5. The model specification for each bank has been determined by ARCH LM tests and an analysis of the correlograms of squared residuals. These indicate that the EGARCH (1,1) specification is the best suited for the great majority of banks considered, with the only exception of Lehman Brothers. This bank presents long term persistence, possibly due to the extreme volatility it was subject to in the months preceding its bankruptcy.

Estimation results show that all ARCH and GARCH terms are statistically significant at 5% and 10% significance level. Almost the same thing happens with the leverage effects coefficient, except for the case of Société Generale, for which there is no evidence of asymmetry. This first set of results is in line with those in Ho *et al.* (2012) and successfully captures the dynamics of stock prices volatility in our sample.

4.2. The Role of Options Trading Volume

Model specifications regarding the inclusion of our option volume variables follow those in Ho et al. (2012), and are presented in equation (4) in Section 2. However, in our specification, the RCALL60, RPUT60 and SVOL series enter the EGARCH equations after a transformation, using their log-differences. This implies that we are studying the impact of trading volume shocks in the volatility of the returns of the underlying stock. In addition, we also estimate a model excluding the stock volume (SVOL), as shown below in equation (4').

$$\log\left(h_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log\left(h_{t-1}\right) + \beta_3 \mathrm{dlog}\left(\mathrm{RCALL60}_t\right) + \beta_4 \mathrm{dlog}(\mathrm{RPUT60}_t) \tag{4'}$$

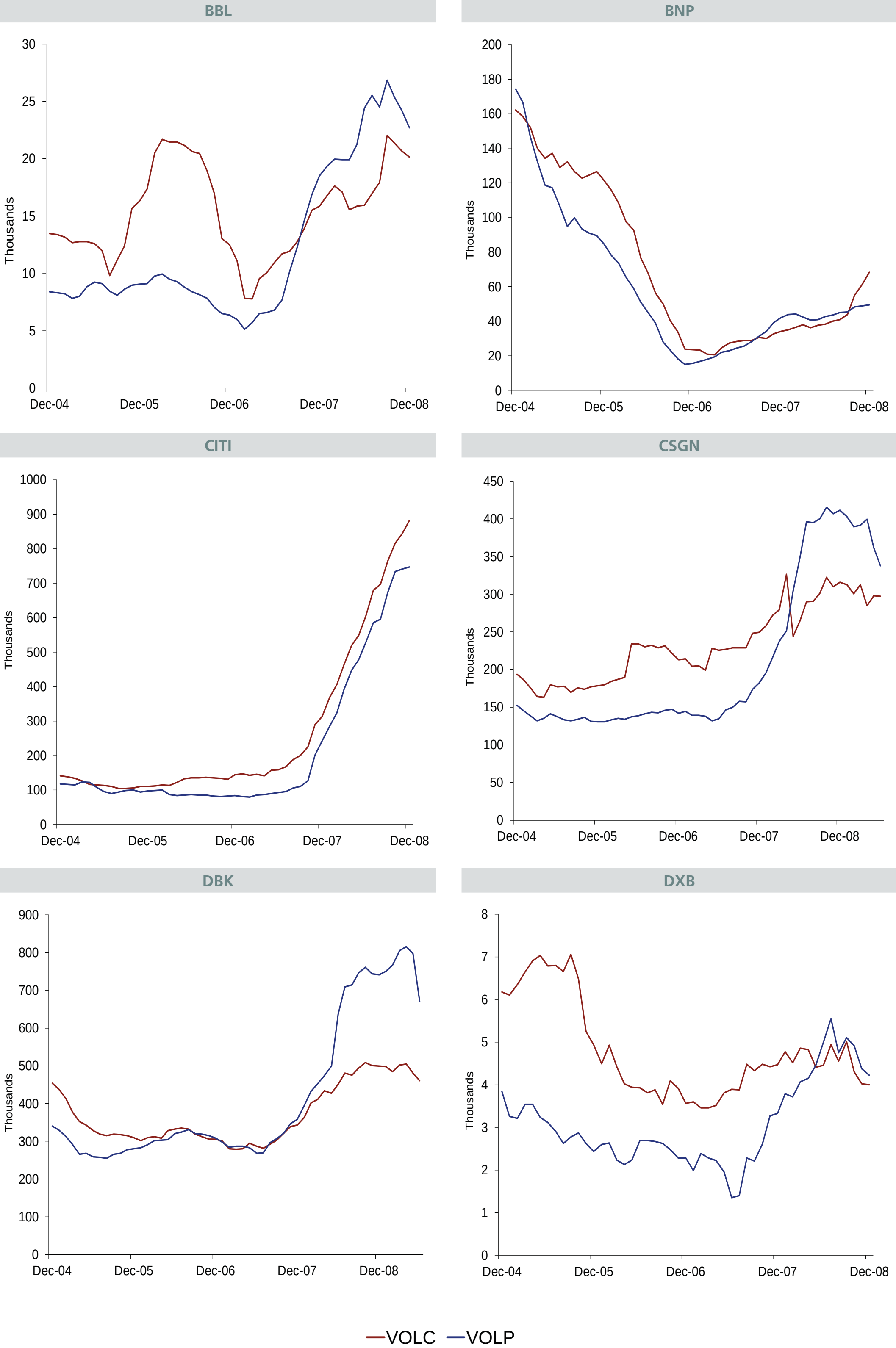
Tables 6 and 7, respectively, report the results of the estimation of models (4') and (4). First, we notice that the growth of option volume holds in general its explanatory power over stock volatility, since for all firms at least one of the two ratios is significant and positive. In fact, only Fortis (FRB) and Lloyds banking Group (TSB) fail to show both call and put variables as significant drivers of volatility.

The explanatory power of option volume appears to become less robust after accounting for stock volume, though. Despite this, only Deutsche Bank (DBK), fails to present a positive and significant coefficient at a 5% significance level for at least one of the two option volume ratios. This result is also particular, as the coefficient for RCALL60 is significant, but actually negative. As for stock volume, CITI is the only exception to the trend that attributes a positive correlation of this variable with volatility.

The EGARCH terms, including the asymmetry coefficient, did not change considerably from the plain EGARCH (1,1) specification in either of these models. There is a slight decrease in the estimates for the coefficients of the ARCH terms, but for all banks the differences are either too small to matter, or there is no discernible trend across all banks that allows us to draw any conclusions. These results are largely in line with findings in Ho *et al.* (2012), both in terms of sign and significance of the option volume coefficients.

Chart 2 (continue)

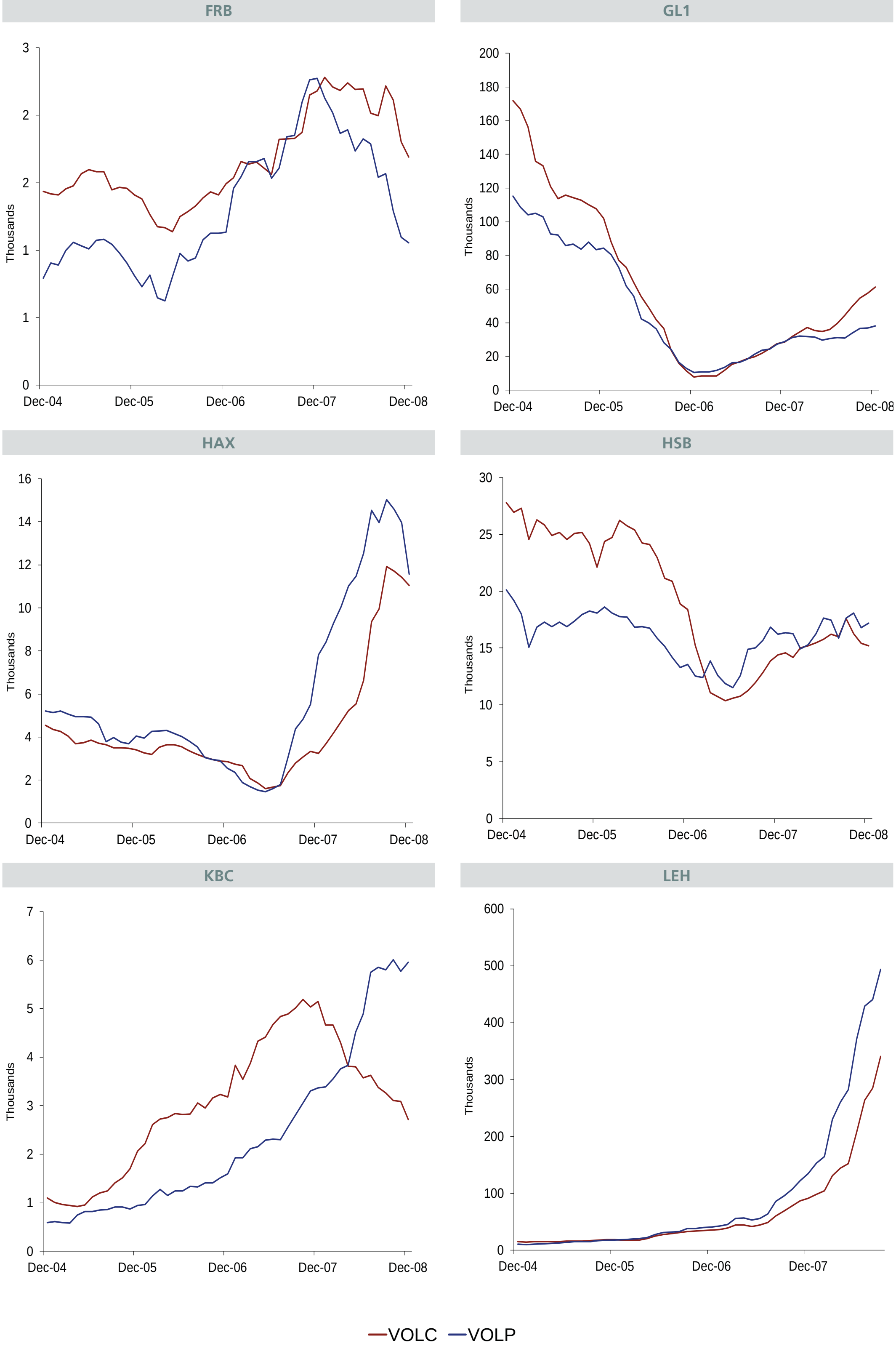
TOTAL CALL (VOLC) AND PUT (VOLP) VOLUME (12 MONTH MOVING AVERAGE)



Sources: Eurex, CBOE and Euronext.

Chart 2 (continuation)

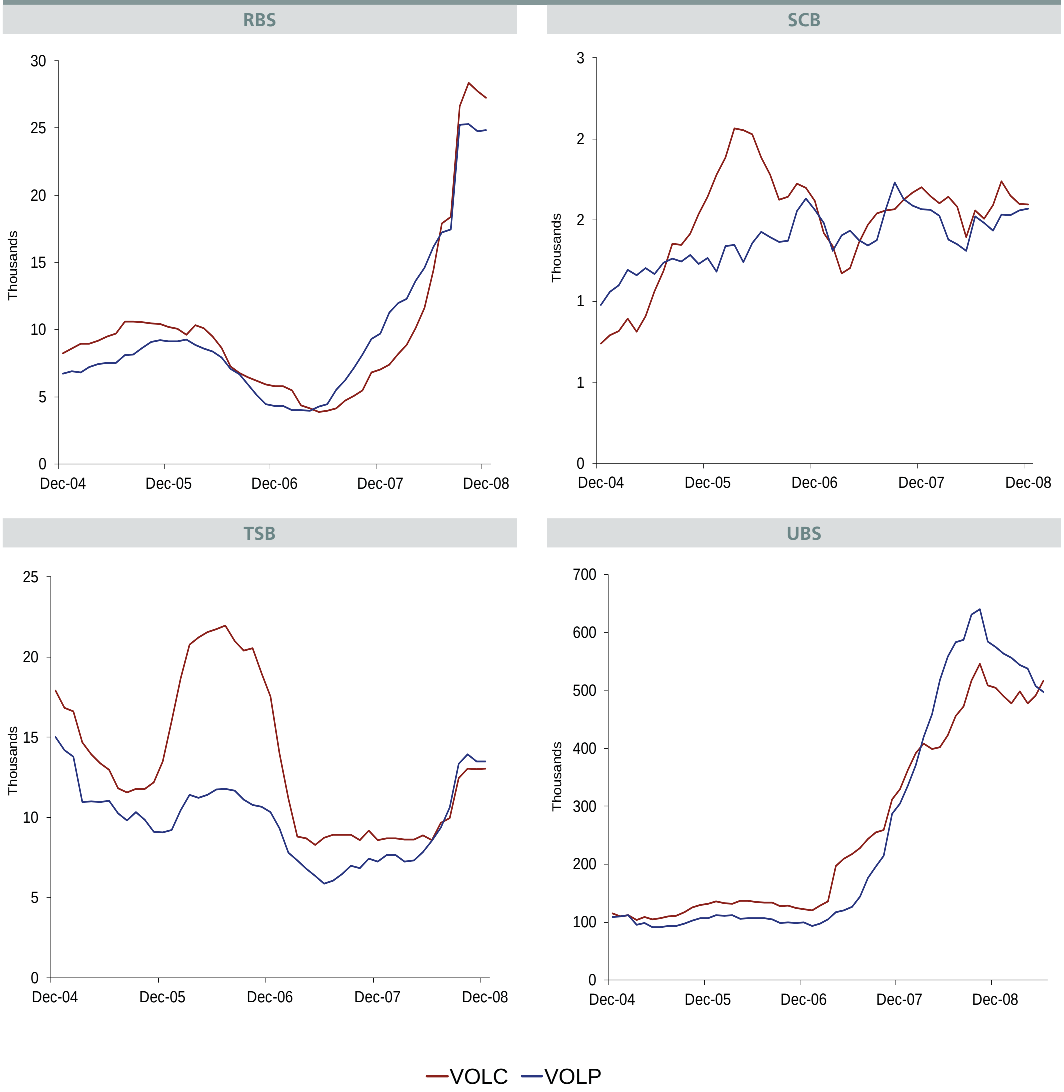
TOTAL CALL (VOLC) AND PUT (VOLP) VOLUME (12 MONTH MOVING AVERAGE)



Sources: CBOE, Eurex and Euronext.

Chart 2 (continuation)

TOTAL CALL (VOLC) AND PUT (VOLP) VOLUME (12 MONTH MOVING AVERAGE)



Sources: CBOE, Eurex and Euronext.

4.3. Accounting for Structural Breaks and Market Volatility

As mentioned in Section 2, sudden shifts in the volatility regime may create distortions in the estimates of the coefficients of the GARCH models and even induce persistence in volatility.

Accordingly, in equation (5) we assess this possibility by introducing two dummies that also capture these shifts through two structural breaks in volatility identified by the CUSUM tests ($SUBP_t$ and $SUBP2_t$).

Table 8 reports the results and shows that, with the exception of Lloyds Banking Group (TSB) and UBS, all banks present at least one break at a 10% significance level. Regarding the 2007 dummy there is a considerable number of banks for which the break in unconditional volatility does not seem to hold explanatory power. Concerning the 2008 dummy, the results are more conclusive, not only are there more banks for which it appears to be a relevant variable, but also, the magnitude of the coefficient is, in general, greater. Comparing the magnitude of both dummy coefficients, we can infer that the increase in volatility from the second regime to the final is, for all banks except HSBC, greater than the one that

Table 5

EGARCH(1,1) WITHOUT EXOGENOUS VARIABLES ASSOCIATED WITH EQUATION (1)

$$\log\left(h_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log\left(h_{t-1}\right)$$

Bank	ω	β1	γ	β2
BLL	**-0.204**	**0.15**	**-0.087**	**0.989**
BNP	**-0.089**	**0.091**	**-0.056**	**0.997**
CITI	**-0.283**	**0.22**	**-0.128**	**0.986**
CSGN	**-0.225**	**0.172**	**-0.056**	**0.988**
DBK	**-0.204**	**0.154**	**-0.076**	**0.989**
DXB	**-0.268**	**0.232**	**-0.053**	**0.989**
FRB	**-2.824**	**0.04***	**-0.118**	**0.532**
GL1	**-0.219**	**0.182**	-0.064	**0.99**
HAX	**-0.209**	**0.182**	**-0.065**	**0.991**
HSB	**-0.136**	**0.121**	**-0.055**	**0.994**
KBC	**-0.169**	**0.137**	**-0.06**	**0.992**
LEH	**-0.351**	**0.297**	**-0.164**	**0.982**
RBS	-0.269	**0.759**	**0.304**	**1.041**
SCB	**-0.257**	**0.177**	**-0.113**	**0.985**
TSB	**-0.231**	**0.187**	**-0.049***	**0.989**
UBS	**-0.194**	**0.165**	**-0.088**	**0.991**

Source: Authors' calculations.

Note: All estimates use the Bollerslev and Wooldridge (1992) heteroskedasticity consistent standard errors. Figures in bold represent coefficients that are significant at the 5% level. Figures in bold with a * represent coefficients that are significant at the 10% level.

occurred from the low volatility regime to the medium volatility regime. This provides statistical evidence that the conditional variance of the returns of these companies suffered, in general, permanent shifts in the vicinity of the events captured by the dummy variables.

Concerning the exogenous variables that were already present in the previous model, changes are mostly negligible, pointing to the fact that the inclusion of the structural breaks does not affect the explanatory power of the three variables linked to trading activity.

Finally, we analyze the estimation results for the model associated with equation (6), in which we try to assess the role of market volatility in explaining the volatility of stock returns and check whether the previous results concerning the trading volume variables still hold.

The estimation results are presented in Table 9. The Market volatility variable is statistically significant for 9 out of the 16 banks under analysis. Most of the British banks, five out of six, actually show a practically null coefficient. This result, coupled with fact that the structural breaks in the previous model failed to capture shifts in volatility for only two banks, leads us to believe that using the dummies may capture the exogenous volatility more accurately.

Nevertheless, regarding stock volume, the coefficients show very little change after including the market volatility variable. For the RCALL and RPUT variables the differences are not very big either. The only cases in which there was some relevant variation was FRB, for which the RCALL variable lost its significance entirely, and DBK where the coefficient for RCALL appears once again significant at a 5% level, like it did in the model without market volatility or structural breaks.

The most relevant impact of including the market volatility variable in the EGARCH coefficients is felt in the asymmetry parameter. The number of banks that present no evidence of leverage effects has lowered from three (BNP, FRB and LEH), in the model with only option and stock volume variables, to only one (LEH) in the model with a market volatility variable.

Table 6

EGARCH(1,1) WITH OPTION VOLUME VARIABLES ASSOCIATED WITH EQUATION (4')

$$\log\left(\mathrm{h}_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{\mathrm{h}_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{\mathrm{h}_{t-1}} + \beta_2 \log\left(\mathrm{h}_{t-1}\right) + \beta_3 \mathrm{dlog}\left(\mathrm{RCALL60}_t\right) + \beta_4 \mathrm{dlog}(\mathrm{RPUT60}_t)$$

Bank	ω	β1	γ	β2	RCALL	RPUT
BLL	**-0.171**	**0.154**	**-0.075**	**0.993**	**0.192**	**0.249**
BNP	**-0.103**	**0.09**	**-0.062**	**0.996**	**0.165**	**0.091**
CITI	**-0.176**	**0.177**	**-0.052**	**0.996**	**1.034**	**0.615**
CSGN	**-0.162**	**0.123**	**-0.06**	**0.992**	**0.633**	**0.565**
DBK	**-0.141**	**0.123**	**-0.078**	**0.994**	**0.448**	**0.335**
DXB	**-0.16**	**0.151**	**-0.06**	**0.995**	**0.157**	**0.132**
FRB	0.002	**0.157**	-0.013	**1.013**	0.052	**0.208**
GL1	**-0.198**	**0.161**	**-0.085**	**0.991**	**0.153**	**0.161**
HAX	**-0.184**	**0.19**	**-0.068**	**0.995**	**0.14**	**0.167**
HSB	**-0.204**	**0.164**	**-0.061**	**0.991**	**0.332**	**0.195**
KBC	**-0.148**	**0.141**	**-0.044**	**0.995**	**0.188**	**0.113**
LEH	0.015	**0.192**	-0.021	**1.019**	**0.489**	**0.697**
RBS	**-0.14**	**0.165**	**-0.064**	**0.998**	**0.143**	**0.192**
SCB	**-0.205**	**0.167**	**-0.105**	**0.99**	**0.085**	**0.185**
TSB	**-0.143**	**0.12**	**-0.066**	**0.99**	**0.031**	0.001
UBS	**-0.158**	**0.145**	**-0.077**	**0.994**	**0.767**	**0.733**

Source: Authors' calculations.

Note: Formulas for RCALL and RPUT variables are presented in equations **(2)** and **(3)**, respectively. All estimates use the Bollerslev and Wooldridge (1992) heteroskedasticity consistent standard errors. Figures in bold represent coefficients that are significant at the 5% level. Figures in bold with a * represent coefficients that are significant at the 10% level.

Table 7

EGARCH(1,1) WITH OPTION AND STOCK VOLUME VARIABLES ASSOCIATED WITH EQUATION (4)

$$\log\left(h_t\right) = \omega + \beta_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2 \log\left(h_{t-1}\right) + \beta_3 \mathrm{dlog}\left(RCALL60_t\right) + \beta_4 \mathrm{dlog}\left(RPUT60_t\right) + \beta_5 \mathrm{dlog}\left(SVOL_t\right)$$

Bank	ω	β1	γ	β2	RCALL	RPUT	SVOL
BLL	**-0.114**	**0.114**	**-0.064**	**0.997**	**0.076**	**0.167**	**1.039**
BNP	-0.012	**0.034**	-0.017	**1.002**	**0.068**	-0.003	**1.688**
CITI	**-0.174**	**0.176**	**-0.051**	**0.996**	**1.013**	**0.602**	0.085
CSGN	**-0.122**	**0.11**	**-0.038**	**0.996**	**0.435**	**0.368**	**1.112**
DBK	**-0.064**	**0.074**	**-0.027**	**1**	**-0.168**	-0.072	**2.309**
DXB	**-0.114**	**0.122**	**-0.059**	**0.998**	**0.073**	**0.067**	**1.083**
FRB	-0.079	**0.107**	-0.04	**1.001**	0.019	**0.048**	**1.617**
GL1	**-0.068**	**0.081**	**-0.031**	**1**	**0.056**	**0.105**	**1.623**
HAX	**-0.157**	**0.168**	**-0.045**	**0.997**	**0.05**	**0.076**	**1.219**
HSB	**-0.143**	**0.126**	**-0.041**	**0.995**	**0.231**	**0.15**	**0.913**
KBC	**-0.069**	**0.094**	**-0.043**	**1**	**0.055**	0.036	**1.399**
LEH	-0.067	**0.16**	0.006	**1.007**	**0.309**	**0.424**	**1.205**
RBS	**-0.071**	**0.098**	**-0.037**	**1.001**	0.06	**0.102**	**1.325**
SCB	**-0.11**	**0.108**	**-0.081**	**0.996**	0.016	**0.105**	**1.022**
TSB	**-0.064**	**0.086**	**-0.038**	**1**	**0.137**	0.04	**1.047**
UBS	**-0.146**	**0.143**	**-0.064**	**0.996**	**0.624**	**0.58**	**0.912**

Source: Authors' calculations.

Note: Formulas for RCALL and RPUT variables are presented in equations **(2)** and **(3)**, respectively. SVOL is the stock trading volume variable. All estimates use the Bollerslev and Wooldridge (1992) heteroskedasticity consistent standard errors. Figures in bold represent coefficients that are significant at the 5% level. Figures in bold with a * represent coefficients that are significant at the 10% level.

Table 8

EGARCH(1,1) WITH VOLUME VARIABLES AND STRUCTURAL BREAKS ASSOCIATED WITH EQUATION (5)

$$\log\left(h_t\right) = \omega + \beta_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + \gamma\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2\log\left(h_{t-1}\right) + \beta_3\text{dlog}\left(RCALL60_t\right) + \beta_4\text{dlog}\left(RPUT60_t\right) + \beta_5\text{dlog}\left(SVOL_t\right) + \beta_6 SUBP_t + \beta_7 SUBP2_t$$

Bank	ω	β1	γ	β2	RCALL	RPUT	SVOL	SUBP	SUBP2
BLL	**-0.338**	**0.096**	**-0.068**	**0.971**	**0.082**	**0.157**	**1.039**	**0.053**	**0.06**
BNP	-0.031	0.02	-0.015	**0.998**	**0.069**	-0.005	**1.676**	0.002	**0.012**
CITI	**-0.331**	**0.178**	-0.044	**0.98**	**1.017**	**0.598**	0.059	**0.043**	**0.043***
CSGN	**-0.217**	**0.116**	**-0.035**	**0.986**	**0.444**	**0.36**	**1.142**	0.012	**0.022***
DBK	**-0.265**	**0.09**	**-0.058**	**0.979**	**-0.146***	-0.083	**2.272**	0.007	**0.076**
DXB	**-0.294**	**0.126**	**-0.065**	**0.979**	**0.07**	**0.065**	**1.099**	**0.033**	**0.067**
FRB	**-0.301**	**0.099**	**-0.064**	**0.976**	0.039	**0.038***	**1.58**	**0.027***	**0.119**
GL1	**-0.126**	**0.064**	**-0.028***	**0.992**	**0.056**	**0.11**	**1.626**	0.011	**0.034**
HAX	**-0.324**	**0.161**	**-0.047**	**0.979**	**0.053**	**0.067**	**1.224**	**0.044**	**0.062**
HSB	**-0.309**	**0.112**	-0.029	**0.978**	**0.218**	**0.15**	**0.931**	**0.041**	0.031
KBC	**-0.368**	**0.093**	**-0.063**	**0.967**	**0.056**	0.02	**1.426**	**0.037**	**0.112**
LEH	**-0.334**	**0.206**	-0.046	**0.98**	**0.494**	**0.534**	**0.413**	**0.034***	**0.565**
RBS	**-0.168**	**0.073**	**-0.045**	**0.988**	0.049	**0.099**	**1.332**	0.025	**0.037**
SCB	**-0.322**	**0.121**	**-0.083**	**0.974**	0.025	**0.1**	**1.025**	**0.03**	**0.054**
TSB	-0.114	**0.059**	**-0.043**	**0.993**	**0.131**	0.037	**1.042**	0.011	0.023
UBS	**-0.161**	**0.145**	**-0.067**	**0.994**	**0.624**	**0.574**	**0.924**	-0.001	0.009

Source: Authors' calculations.

Note: Formulas for RCALL and RPUT variables are presented in equations **(2)** and **(3)**, respectively. SVOL is the stock trading volume variable. SUBP and SUBP2 are dummies included to capture the structural breaks in volatility in July 2007 and October 2008. All estimates use the Bollerslev and Wooldridge (1992) heteroskedasticity consistent standard errors. Figures in bold represent coefficients that are significant at the 5% level. Figures in bold with a * represent coefficients that are significant at the 10% level.

Table 9

EGARCH(1,1) WITH VOLUME VARIABLES AND MARKET VOLATILITY ASSOCIATED WITH EQUATION (6)

$$\log\left(h_t\right) = \omega + \beta_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + \gamma\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_2\log\left(h_{t-1}\right) + \beta_3\text{dlog}\left(RCALL60_t\right) + \beta_4\text{dlog}\left(RPUT60_t\right) + \beta_5\text{dlog}\left(SVOL_t\right) + \beta_6 MVOL_t$$

Bank	ω	β1	γ	β2	RCALL	RPUT	SVOL	MVOL
BLL	**-0.145**	**0.115**	**-0.065**	**0.994**	**0.077**	**0.166**	**1.044**	0.000
BNP	**-0.121**	**0.033**	**-0.028***	**0.991**	**0.071**	0.000	**1.683**	**0.001**
CITI	**-0.294**	**0.182**	**-0.048***	**0.986**	**1.028**	**0.611**	0.000	**0.002**
CSGN	**-0.323**	**0.115**	**-0.026***	**0.978**	**0.447**	**0.346**	**1.192**	**0.002**
DBK	**-0.468**	**0.090**	**-0.035**	**0.964**	**-0.173**	0.000	**2.324**	**0.004**
DXB	**-0.209**	**0.123**	**-0.062**	**0.990**	**0.071**	**0.069**	**1.114**	**0.001**
FRB	**-0.524**	**0.123**	**-0.065**	**0.963**	0.000	**0.047**	**1.621**	**0.005**
GL1	**-0.173**	**0.068**	**-0.035**	**0.989**	**0.057**	**0.110**	**1.644**	**0.001**
HAX	**-0.172**	**0.168**	**-0.046**	**0.996**	**0.050**	**0.076**	**1.221**	0.000
HSB	**-0.217**	**0.126**	**-0.038***	**0.988**	**0.229**	**0.150**	**0.914**	0.000
KBC	**-0.413**	**0.126**	**-0.055**	**0.971**	**0.059**	0.000	**1.435**	**0.003**
LEH	1.201	**0.159**	0.000	**1.007**	**0.309**	**0.425**	**1.201**	0.000
RBS	**-0.108**	**0.100**	**-0.036**	**0.998**	0.000	**0.108**	**1.347**	0.000
SCB	**-0.235**	**0.123**	**-0.086**	**0.985**	0.000	**0.103**	**1.036**	**0.001***
TSB	**-0.090**	**0.074**	**-0.040**	**0.997**	**0.138**	0.000	**1.064**	0.000
UBS	**-0.183**	**0.145**	**-0.063**	**0.993**	**0.623**	**0.574**	**0.932**	0.000

Source: Authors' calculations.

Note: Formulas for RCALL and RPUT variables are presented in equations **(2)** and **(3)**, respectively. SVOL is the stock trading volume variable. MVOL is a measure of market wide volatility (VIX index for English and American banks and VSTOXX index for all others). Figures in bold represent coefficients that are significant at the 5% level. Figures in bold with a * represent coefficients that are significant at the 10% level.

5. Conclusion

This article studies the link between the trading activity in banks equity options market and the volatility of the corresponding underlying stock. Our approach differs from previous work in three main aspects. First, our focus rested upon option trading volume, rather than implied volatility. Second, our sample is unique both in terms of sector and geography, since our sample includes only large banks coming from various countries on both sides of the Atlantic. Finally, and most importantly, our sample is also very diverse concerning different patterns of volatility that emerged as a consequence of a period of financial crisis, allowing us to study the dynamics created by this fact.

Using conditional volatility models, we are able to capture the dynamics of the volatility of most of the stocks in our sample. In addition, we check the robustness of our models by identifying sudden changes in the pattern of volatility during the period under analysis for all banks, caused by the subprime crisis, in two alternative ways. First, we introduce dummy variables to capture these breaks. As an alternative, we also included a market volatility variable to capture the volatility changes that are common to the entire market.

The results show the presence of breaks in volatility in both models. The results of the various models are consistent with the fact that both stock trading volume and option trading volume have a statistically significant and positive impact on volatility, meaning that the more options are traded in a given day, the more likely it is that the stock return will be very high or very low. This result shows that investors may be trading private information about volatility in the option market. This can be important in understanding the interconnectedness between the two markets, contribute to better model the volatility of stock returns and potentially help to predict market instability.

For this reason, future extension of this research should address the forecasting potential of this relation, in order to incorporate this information in a forward-looking model of market volatility.

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