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How does liquidity react to stress periods in a limit order market?

Helena Beltran (*)
Alain Durré (**)
Pierre Giot (***)

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(*) Helena Beltran is a FRNS research fellow at CORE, Université catholique de Louvain, Voie du Roman Pays 34, BE-1348 Louvain-la-Neuve. e-mail: beltran@core.ucl.ac.be

(**) Alain Durré is from the Institut d'Économie Scientifique et de Gestion of the Catholic University of Lille (France), member of the LABORES (CNRS-U.R.A. 362) and member of the Research Department of the National Bank of Belgium. e-mail: alain.durré@nbb.be

(***) Pierre Giot is Professor of finance at the Department of Business Administration & CEREFIM, University of Namur, Rempart de la Vierge 8, BE-5000 Namur and CORE at Université catholique de Louvain. e-mail: pierre.giot@fundp.ac.be

Send all correspondence to beltran@core.ucl.ac.be

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Editorial

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Abstract

This paper looks at the interplay of volatility and liquidity on the Euronext trading platform during the December 2, 2002 to April 30, 2003 time period. Using transaction and order book data for some large- and mid-cap Brussels-traded stocks on Euronext, we study the ex-ante liquidity vs volatility and ex-post liquidity vs volatility relationships to ascertain if the high volatility led to decreases in liquidity and large trading costs. We show that the provision of liquidity remains adequate when volatility increases, although we do find that it is more costly to trade and that the market dynamics is somewhat affected when volatility is high.

JEL-code : G10, C32

Keywords: order book, volatility, liquidity

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I. Introduction

Modelling and appraising liquidity in financial markets has been of paramount importance for central banks, regulators and practitioners for the last decade. The perceived liquidity decrease during the financial crisis of 1998 has led many to question the functioning of stock markets during stress periods. Moreover, the well-publicized problems of large hedge funds such as LTCM have also pointed out that liquidity could dry out rapidly during crisis periods, hence normal market conditions do not offer much information regarding what happens during volatile periods. As pointed out in the empirical and theoretical literature, liquidity depends crucially on the market structure. In price-driven markets (e.g. at the NASDAQ or in bond and FOREX markets), a market maker ensures the continuity and viability of the trading process by quoting firm bid and ask prices whatever the market conditions. Thus, the inside spread (i.e. the difference between the best buy and sell prices) and depth at the best quotes seem to be good measures of the available liquidity, that is on an ex-ante basis. Ex-post, the liquidity of an exchange is often assessed by computing measures such as the effective or realized spread, or VWAP (volume-weighted average price) measures. Note that measures related to the liquidity displayed by the order book refer to pre-trade liquidity, and will correspondingly be referred to as ex-ante liquidity measures. Examples of such measures are the quoted spread and bid/ask depths. Measures computed with transaction data refer to realized trading costs, thus called ex-post liquidity measures. Effective spread is a well-known example of an ex-post liquidity measure.

In pure order-driven markets, no market maker stands ready to trade. Liquidity is thus provided by limit orders entered throughout the day by 'patient' or liquidity supplier investors (often value investors), and orders are executed only when prices match, i.e when liquidity is demanded by 'impatient' or liquidity demander investors. Examples of impatient traders include traders who wish to transact near the close of the trading session (so that the price of their trade is not far from the official closing price), see Cushing and Madhavan (2000), or momentum traders who are keen on entering immediate long or short positions (Keim and Madhavan, 1997). Therefore, the inside spread is not as relevant as in price-driven markets and depth outside the quotes (i.e. the complete state of the order book) and times between order entry and execution (the immediacy component) become crucial. As shown in Handa and Schwartz (1996), and discussed below, there exists a dynamical equilibrium between limit order and market order trading which strongly determines the available liquidity of the order book.

While in a price-driven market the market makers ensure the continuity of the price process (for example specialists at the NYSE are required by the exchange to maintain an ‘orderly market’), in order-driven markets no investors have to provide liquidity. Thus it is not inconceivable that order book systems could break down in times of stress because the dynamical equilibrium of Handa and Schwartz (1996) between limit orders and market orders is disrupted. Which trading platform best performs in such time periods? Some argue that the main advantage of price-driven platforms is the presence of market makers who always have to deal, even during highly disturbed periods. On the contrary, as no market participant has to submit limit orders in order-book markets, it is likely that, during periods of stress, fewer limit orders are entered into the book. This then decreases liquidity.[1] On the other hand, it could be argued that the heterogeneity of liquidity providers in order-driven markets is indeed a strong advantage as it leaves room for ‘contrarian’ traders to submit orders. These traders, unlike market makers, are not constrained by inventory holding issues and they may have a long-term vision that incites them to enter positions which go against the current market trend (for an example of such behaviour in the FOREX market see the report “Structural aspects of market liquidity from a financial stability perspective” by the Committee on the Global Financial System, 2001). Indeed, the presence of enough contrarian traders could lead to increased order-book market liquidity than in a (pure) specialist market trading system during periods of stress.[2]

Finally, a key issue for central banks and regulators is how the market maker system and computerized order book system behave in periods of stress.[3] As argued in Mishkin and White (2002), stock markets are influenced by monetary policy but are mainly driven by fundamentals or animal spirits. Central banks have therefore few instruments at hand to influence the way markets behave. For central banks and regulators the key issue is then to understand the liquidity dynamics in order to develop prudential rules (for instance by imposing a market structure) that prevent and anticipate the buildup of liquidity crises and price disruptions.

In this paper we analyze how liquidity is affected by increases in volatility for some stocks traded on the Euronext trading platform during the time period that ranges from December 2, 2002 to April 30, 2003. A period with a high level of volatility will be referred to as a “stress period”,

[1] Another concern is the ability of order books to provide liquidity for large orders without big price discrepancies (hence the recurrent use of upstairs or block markets for large trades in order book markets). This is not the focus of the current study.

[2] In case of extreme volatility events, such as on September 11th, 2001, few contrarians would be ready to act as a counterparts. Thus it is likely that liquidity dries out in the book whereas the specialist has to ensure the continuity of the trading process.

[3] See Borio (2000) and the report “The implications of electronic trading in financial markets” by the Committee on the Global Financial System (2001).

while low-volatility periods are referred as “normal periods”. Note that, contrary to most papers dealing with high volatility periods, we do not focus on one (or succession of) extreme event(s). For some days during that time frame, volatility was unusually large as market participants anticipated the start of the second Gulf war and markets were quite jittery till the end of the conflict. The last month of 2002 and the first months of 2003 (i.e. just before the start of the war) were truly horrible months for stock investors as most stock indexes (and especially European stock markets) were in a free fall. The end of the conflict in Irak led to a complete turnaround for stock markets as investors rushed to buy (then deemed oversold) equities. Using high-frequency trade and order book data, we analyze the liquidity and volatility exhibited by some large- and mid-cap Brussels traded stocks on the Euronext platform. We study more particularly the ex-ante liquidity vs volatility and ex-post liquidity (effective spread for example) vs volatility relationships to ascertain if the high volatility led to decreases in liquidity and large trading costs. From an econometric point of view, the low and high-volatility regime states will be determined according to an endogenous classification rule based on Markov switching models. Besides the ex-ante and ex-post assessment of liquidity, we also estimate VAR models for some of the variables measured on an intraday basis. Thereafter, we assess the impulse response functions derived from these estimated VAR models and analyze the dynamics of liquidity. Because we choose large- and mid-cap stocks for which there are no market makers, we thus shed light on the ex-ante and ex-post liquidity vs volatility relationships in a pure automated auction market.

The results indicate that, while ex-ante or ex-post trading costs somewhat increased with volatility, liquidity remained high (trading costs were ‘reasonable’) and the trading process did not break down. The dynamical analysis based on the VAR model presented in the second part of the paper offers a balanced view according to which the volatility regime bears moderately on the dynamics of the liquidity provision. As such and anticipating on the conclusion of the paper, our results seem to indicate that there is no real important deterioration in the provision of liquidity when volatility increases, although we do find that it is more costly to trade when volatility is high and that the market dynamics is somewhat affected.

The rest of the paper is structured as follows. After this introduction, we present a review of the literature in Section II. The Euronext trading system and the dataset are discussed in Section III. The first part of the empirical analysis is presented in Section IV, while the trading dynamics is given in Section V. Finally, Section VI concludes.

II. Review of the literature

A. Automated auction markets, liquidity and volatility

The literature on market microstructure has traditionally focused on dealership markets. Indeed, most of the models surveyed in O'Hara (1995) focus on the behavior of market makers or deal with fixed costs, inventory costs or asymmetric information costs models in the framework of market maker based trading systems. Because of the growing popularity of automated auction systems in European countries or in the electronic trading systems in the United States, there is now a rapidly evolving literature on order book markets.[4] Most of the empirical studies in that field focus on the provision of liquidity in automated auction markets. Indeed, as no market makers stand ready to buy and sell the traded assets in this setting, the viability of pure electronic order book markets and the ability to trade at all times are far from ascertained. Crucially, the provision of liquidity in times of crisis is of paramount importance. We thereafter survey some of the recent empirical work that focuses on the provision of liquidity in order book markets, the relationship between volatility and liquidity and the characteristics of automated auction markets in times of crisis.

In an important extension of pure dealership markets, automated auction markets allow a relatively easy ex-ante characterization of liquidity beyond the inside bid-ask spread. Because the state of the order book is usually fully or partially made available to market participants, price impact curves (i.e. unit bid and ask prices for a given volume, also called costs of buy and sell trades by Irvine, Benston, and Kandel, 2000) can be computed which allow the computation of extended liquidity measures such as the cost of buy or sell trades. These measures, popularized in Irvine, Benston, and Kandel (2000), Martinez, Tapia, and Rubio (2000), Coppejans, Domowitz, and Madhavan (2002) or Beltran, Giot, and Grammig (2003), aggregate the status of the order book at any given time and offer a relatively accurate picture of the available ex-ante liquidity, i.e. before the submission of a buy or sell trade.[5]

In a now seminal paper, Biais, Hillion, and Spatt (1995) provide one of the first empirical analysis of a limit order book market (the Paris Bourse). They study the joint dynamics of the order flow (placement of market or limit orders) and the order book: investors place limit (market) orders

[4] See the book by Harris (2002).

[5] In dealership markets, the ex-ante available liquidity often reduces to the best bid and ask prices (or quoted spread), and the available depth at these prices. Effective spreads or realized spreads are ex-post liquidity measures as they are computed after the submission of the buy or sell trade.

when the bid-ask spread is large (small) or the order book is thin (thick). Therefore, "investors provide liquidity when it is valuable to the marketplace and consume liquidity when it is plentiful". They also show that there is a strong competition among traders (who monitor the state of the order book) to provide liquidity as the flow of order placements is concentrated at or inside the bid-ask quote and the corresponding limit orders are placed in quick succession. For stocks traded on the pure electronic limit order platform of the Hong Kong stock exchange, Ahn, Bae, and Chan (2001) investigate the 'ecological' nature of the pure order driven market such as put forward in Handa and Schwartz (1996). They show that there exists a dynamical equilibrium between limit order trading and transitory (or short-term) volatility: market depth rises subsequent to increases in transitory volatility and transitory volatility declines subsequent to increases in market depth. Indeed transitory volatility attracts the placement of limit orders (instead of market orders) which therefore add liquidity to the order book. They also show the need to separate volatility at the ask and bid sides of the order book: when transitory volatility arises from the ask (bid) side, investors submit more limit sell (buy) orders than market sell (buy) orders. On a related topic and for NYSE stocks, Bae, Jang, and Park (2003) show that it is important to distinguish between transitory and informational volatility: "a rise in transitory volatility induces a new placement of limit orders. A rise in informational volatility appear neither to increase nor decrease the placement of limit orders relative to market orders". Using a Probit model applied to Swiss stocks traded on the Swiss Stock Exchange, Ranaldo (2004) presents quite similar results: orders are more aggressive (i.e. traders submit more marketable limit orders than just plain limit orders) when the order queue on the incoming trader's side of the book is larger. For example, buyers then face a smaller execution probability and have to raise their order aggressiveness. The opposite is true for sellers. Moreover, temporary volatility and larger spreads imply weaker trading aggressiveness. Note however that these studies do not focus on times of crises and it is thus not clear whether they would get similar results when trading is hectic.

Danielsson and Payne (2001) study the dynamics of liquidity supply and demand in the Reuters D2000-2 order book trading system.[6] They focus on the interaction between market and limit orders and show that the probability of a limit buy (sell) order is relatively low after a market sell (buy). Therefore, there could be strong fluctuations in the provision of liquidity because of the complex interplay between market and limit orders (what they call dynamic illiquidity). In agreement with Foucault (1999), they show that the fraction of limit orders in total order arrivals increases

[6]The Reuters D2000-2 system is an electronic order book system designed for inter-dealer FOREX trades.

with volatility (which increases liquidity), although the bid-ask spread also increases with volatility (which decreases liquidity). Hence, increases in volatility yield wider bid-ask spreads and lead to the increased placement of limit order relatively far from the quote mid-point. They also show that market participants react strongly to the unanticipated component of volume (predictable volume increases liquidity, unpredictable decreases liquidity). This hints at the importance of asymmetric information in automated auction markets and suggests the need for extensions of the models by Glosten and Milgrom (1985) and Easley and O'Hara (1987).

Goldstein and Kavajecz (2000) focus on the liquidity provision at the New York Stock Exchange during extreme market crises. Indeed, they deal with the very short time period that surrounds October 27, 1997. On that day, the Dow Jones Industrial Average lost 554 points (which triggered the circuit breakers) and on October 28, 1997 the index shot up by 337 points. They examine the liquidity supplied by the limit orders (routed by the SuperDOT order book trading system) and by the NYSE market participants (specialists and floor brokers). They show that a substantial liquidity drain occurred on the day after the market crash (i.e. on October 28, 1997) as the order book exhibited continuous large spreads and poor depth. However, the overall market liquidity did not drop dramatically as the specialists and floor brokers fulfilled their functions of liquidity providers and thus ensured good overall depth and low spreads at the NYSE. This hints at the adequacy of hybrid[7] market structures and shows that the viability of pure automated auction markets in times of crisis can be threatened by the significant drop in liquidity (due to the substantial fall in the number of limit orders entered in the trading system). Note that Venkatamaran (2001) also stresses the merits of hybrid trading structures which lead to reduced trading costs. This literature is also closely connected to the literature on block trading. For example, Bessembinder and Venkatamaran (2001) show that the upstairs (block trading) market at the Paris Bourse provides a key role in facilitating large trades. The dealership type block trading structure thus provides considerable additional liquidity beyond the liquidity supplied by the pure limit orders entered in the order book.

The study by Chordia, Sarkar, and Subrahmanyam (2002) focuses on the commonality in liquidity for stocks and bonds markets.[8] Not surprisingly, they show that the correlation between stock and bond market liquidity (proxied by OLS innovations in their linear regressions of daily liquidity measures) sharply increases during periods of crises. This indicates greater simultaneous bond and

[7]A hybrid trading structure combines features of order book markets (the existence of a centralized order book run by a computer system) and of dealership markets (the existence of market makers or floor brokers). A good example of such a structure is the NYSE, see for example Bauwens and Giot (2001) or Sofianos and Werner (2000).

[8]Chordia, Roll, and Subrahmanyam (2001a) and Chordia, Roll, and Subrahmanyam (2001b) focus on the commonality in liquidity for a large set of stocks traded on the New York Stock Exchange.

stock investor uncertainty during periods of crises and shows that the loss of liquidity in times of crisis is systemic in nature. Note that liquidity commonality (either across stocks traded at the same venue, or across both stocks and bonds in a given country or in a set of countries) poses a problem to diversification strategies as 'standard' mean-variance analysis does not take into account liquidity commonality when efficient frontiers are computed. Domowitz and Wang (2002), as an extension of Amihud and Mendelson (1986), focus on this issue and show that liquidity commonality is strongly shaped by order (market vs limit orders) types. Finally, Chordia, Roll, and Subrahmanyam (2002) focus on order imbalances (buy orders less sell orders) and show that, for aggregated intraday NYSE data at the daily level, order imbalances decrease market liquidity.

Most empirical studies thus conclude that the 'ecological' nature of the pure order driven market works quite well: traders enter limit orders when liquidity is needed and are more impatient when liquidity is plentiful. Automated auction markets are also quite cheap to run, and bid-ask spreads for small to medium trades are quite low (see also Degryse, 1999). It is however not clear whether these results hold in all circumstances. Indeed, almost all studies on automated auction markets focus on the provision of liquidity in normal periods, i.e. not in times of crisis. In that latter case, liquidity could rapidly deteriorate if the sole provision of liquidity comes from limit orders (i.e. in the absence of hybrid systems that allow some provision of liquidity by market makers). Note also that the literature on the placement of limit orders and market volatility works with the hypothesis of 'normal'/transitory market volatility. In periods of crisis where market volatility increases significantly and stays at high levels for many days or weeks, the 'volatility attracts limit orders' relationship should perhaps be qualified. These are however working hypotheses that deserve to be investigated.

B. The regulator's point of view

During the nineties, the growing concern in monetary economics has been the opportunity for monetary authorities to react to stock market crashes and financial distress. The key question is whether Central Banks should have a prudential role in targeting financial stability. This is clearly relevant as history is plentiful of periods where financial instability involved macroeconomic instability. According to this paradigm, a financial crisis, because it acts for instance on the solvability of financial intermediaries, could affect the activity of firms through credit rationing, also called the credit crunch.[9] See Bernanke and Gertler (1995) and Bernanke and Gertler (1999). A key underpinning of this rationale is that price and financial stability are symbiotic in order to maintain a sustainable non inflationary growth. Solow argued that Central Banks should aim for financial stability as a larger risky asset volatility increases the probability of failure for financial institutions. If the Central Bank does not include the financial stability criterium as a monetary policy target, an increasing number of failures is to be expected which would be costly for the economy.[10] In the same vein and because the potential vulnerability of financial systems increases the probability of huge and costly crises (Borio, 2003), Borio and Lowe (2002) call for the inclusion of a financial target along the usual macroeconomic targets. Of course, this issue is controversial because it implies an ability to determine an equilibrium level for financial prices (Cecchetti, Genberg, Lipsky, and Wadhwani, 2000 and Borio and Lowe, 2002) discuss this problem). Note also that theoretical models and discussions of this problem (Bernanke and Gertler, 1999 and Borio and Lowe, 2002) yield ambiguous results and raise the issue of the choice of the financial asset whose price must be monitored.

Recently, Mishkin and White (2002) analyze fifteen historical episodes of stock market crashes in the US and examine the aftermath of these crises. Interestingly, their study suggests that stock market crashes by themselves do not involve financial instability. They show that the state of the financial system and the nature of stress in financial markets seem to be important. In particular, rapidly falling stock prices in conjunction with decreasing liquidity may be particularly destabilizing.[11] Therefore, as a first step towards a prudential role of monetary authorities, a comprehensive understanding of the dynamics of liquidity during stress periods is warranted. Moreover, a closer look at the relationship between liquidity and volatility in times of crisis sheds light on key issues relevant to Central Banks and regulators in the future.

[9] An example is the constraint in the real activity in Japan from 1992 onwards.

[10] See Bernanke and Gertler (1999), Cecchetti, Genberg, Lipsky, and Wadhwani (2000) or Durré (2003) for a discussion.

[11] Mishkin and White (2002) point out for instance that the responses of the Federal Reserve during the stock market declines in 1929 and 1987 were more appropriate than during the recent decline which began in 2000.

III. The Euronext platform and the dataset

A. Trading on the Euronext platform

Euronext encompasses five exchanges, namely the Amsterdam, Brussels, Lisbon, Paris exchanges and the LIFFE. Euronext aims to put forward a unique electronic trading platform for all financial assets. This is already the case for equities trading, as the same trading platform is now used by all exchanges. Trading on the Euronext platform takes place from 9 to 5.25 p.m CET. Limit orders are matched according to the standard price and time priority rules. Market orders (also called marketable limit orders) are executed against the best (in terms of price) prevailing order on the opposite side of the book. If there is not enough volume to fully execute the incoming order, the remaining part of the order is transformed into a limit order at the best price. Traders can also use more sophisticated orders, e.g. fill-or-kill orders (the limit order is either fully executed or cancelled), must-be-filled orders (the market order is completely executed, whatever the price), iceberg orders (part of the volume is not displayed in the book),…Block trading is allowed for large volume trades (the size of these trades is larger than the stock specific minimum block size, called “Taille normale de bloc”). Although the block trade formally takes place outside the book (akin to the upstairs market at the NYSE), the transaction price is actually constrained by the available liquidity in the book. Indeed, Euronext displays throughout the day the hypothetical prices for a sell and a buy order with a volume equal to the minimum block volume. No blocks can be traded at a price outside these limits. Besides block trades, Euronext also allows so-called iceberg (or hidden) orders. As the name suggests, a hidden limit order is not (fully) visible in the order book. This implies that if a market order is executed against a hidden order, the trader submitting the market order may receive an unexpected price improvement. As on other automated auction exchanges (XETRA, Toronto stock exchange,…), iceberg orders have been allowed to heed the request of investors who were reluctant to see their (potentially large) limit orders openly revealed in the order book.[12]

At the start of the trading day and before the regular continuous trading, a pre-opening auction takes place: limit orders are submitted and a start-of-day auction sets the opening price; all orders not executed at the end of the opening period remain in the order book.[13] Throughout the trading day, achievable trade prices are bounded by a static and a dynamic price limit. The static bounds

[12]See D’Hondt, De Winne, and Francois-Heude (2002) for a description of hidden orders on the Euronext trading platform.

[13]See also Biais, Hillion, and Spatt (1999).

are set immediately after the opening auction: they are equal to the auction price +- 10%. During the day, if a trade takes place outside these static bounds, trading is stopped and a new auction takes place (for a time period of 5 minutes). This auction final price defines new static bounds, used thereafter. The second type of bounds are dynamic: a trade cannot take place at a price larger (smaller) than the last trade price plus 2% (minus 2%). If orders can be matched at a transaction price outside the dynamic bounds, the trade is not executed and trading is stopped. A new auction takes place and defines new static and dynamic bounds. A final auction occurs between 5.25 and 5.30 p.m., followed by an additional 10-minute period where traders can trade at the price set by the end-of-day auction.

Note that, depending on the stock, two different Euronext members are involved in the trading process: brokers (called “Négociateurs”) and market makers (called “Animateurs de marché”). All stocks do not feature a market maker. Indeed, stocks belonging to the Euronext 100 index (the first 100 Euronext stocks which have the largest market capitalizations) don’t feature any market maker. Nevertheless, market makers are still allowed to enter orders for these stocks, but then they are considered as simple brokers.

B. The dataset

We were granted access to two historical datasets (for Brussels-traded stocks over a period ranging from December 2, 2002 to April 30, 2003) by Euronext. The first dataset contains the limit order book (LOB) as available to market participants who are not formally Euronext members, i.e. the historical real-time feed of the 5 best orders (price, total volume at that price and number of standing limit orders at that price) on the bid and ask sides of the order book. Indeed, all order book events (order entry, cancellation,...) are time-stamped to the second and lead to a potential order book modification, which is recorded in real-time by Euronext. We thus have snapshots of the 5 best bid and ask limit orders in real-time over the historical period we work with. It should however be stressed that the hidden portion of the iceberg orders is not included in the dataset. As discussed below, this will impact some of our conclusions (regarding the available ex-ante liquidity in the order book for example), while others should not be affected (the ex-post assessment of trading costs for example). The second dataset contains all transactions, more specifically the prices and volumes of the trades time-stamped to the second. Moreover, we also know if the orders matched in the transaction were so-called client or proprietary orders (the two most frequent cases), or market maker orders (a third possibility).[14] Note that the LOB dataset sometimes contains errors as the ordering of prices is not always enforced (e.g. the best ask price is sometimes larger than the ask price ranked second). These errors amount to less than 2% percent of all LOB observations and are removed from the dataset. Furthermore, the trades dataset did not give any information on the side (buy or sell) from which the trade originated. By using the LOB data, we are however able to determine rigourously the sign of the trade, as trades can only occur at the prices displayed in the book. Thus we did not have to rely on the Lee and Ready (1991) algorithm as used by most authors who work with NYSE data.

In this study we focus on three large-cap Belgian stocks (Dexia, Electrabel and Interbrew) and three mid-cap Belgian Stocks (KBC, Solvay and UCB).[15] The first three stocks are characterized by a very large trading activity and are well-known blue-chip stocks widely held by individual and institutional investors. The three mid-cap stocks are also quite actively traded stocks. All six stocks are members of the BEL20 stock index (which features the most 'representative' stocks of the Belgian economy) and no market maker ("animateurs de marché") is involved in the trading of any of these stocks. Descriptive characteristics for the six selected stocks are given in Table I. The stock prices for each stock are plotted in Figure 1.

IV. Empirical analysis

A. The importance of intraday seasonality

Most empirical studies on high-frequency data (Engle and Russell, 1998; Bisière and Kamionka, 2000; Bauwens and Giot, 2001; Bauwens and Giot, 2003) stress the need to correctly model the intraday seasonality exhibited by this kind of data. Indeed, when modelling the volatility, the traded volume, or the spread on an intraday basis, it is of paramount importance to proceed along a four-step procedure: (1) define regularly time-spaced measures of interest (e.g. working at the 15-minute frequency, the 15-minute return volatility, the 15-minute traded volume, the average effective spread over the 15-minute interval,...); (2) compute the time-of-day pattern for each measure; (3) desea-

[14] A so-called client order is an order routed to a Euronext member for execution by an outside investor. A proprietary order is executed by a Euronext member for his own trading account.

[15] This classification of large- and mid-cap stocks is relevant for average European investors. US investors (and more particularly large institutional investors) would consider all these stocks to be only mid-cap stocks, and some of these even almost small-cap stocks.

sonalize each measure by its respective time-of-day pattern; (4) model the deseasonalized variable using an econometric model. Failure to recognize the importance of steps (2) and (3) often lead to incorrect model estimations (see Andersen and Bollerslev, 1997, for an application to the modelling of intraday volatility). Moreover there is also an economic justification in the modelling of the intraday seasonality. Because market participants are actively involved in the day-to-day market action, they know and expect a given pattern of activity (or volatility, spread,...) and are only affected by deviations (or surprises) from what was expected. A well-known example is the reaction of economic agents to news announcements: by itself, the news (e.g. the CPI number in the US) is not really relevant; what matters is the difference between the actual number and the expected number (see e.g. Bauwens, Ben Omrane, and Giot, 2003 or Andersen, Bollerslev, Diebold, and Vega, 2003).

As a illustration, we plot in Figures 2 to 5 the time-of-day pattern for the (annualized) volatility of the 15-minute returns, the 15-minute average traded volume, the relative quoted spread, the current and effective spread (on the same figure), the bid and ask quoted depth, the price impacts for the bid and ask sides, and the trade aggressiveness. Quoted spreads, effective spreads and the quoted ask and bid depths are defined as usual, see Harris (2002). Note that, because we deal with an automated auction market, the effective spread can be larger than the quoted spread, as some transactions walk up the book and thus transaction prices are larger than the quoted spread. The current spread is the quoted spread as observed before the transaction takes place (thus a comparison with the quoted spread allows to assess the extent of traders' market timing). Price impacts capture the premium paid by traders when the transaction is executed against standing limit orders beyond the best quotes. Formally, the average price paid per share for a sell of a v shares at time t is

$$b_t(v) = \frac{\sum_{i=1}^{k} p_i v_i}{\sum_{i=1}^{k} v_i} \tag{1}$$

with $\sum_{i=1}^{k} v_i = v$, and $p_i(v_i)$ the ith bid price (volume) available in the book. The bid price impact is then defined as

$$bp_t(v) = \frac{b_t(1) - b_t(v)}{b_t(1)} * 100. \tag{2}$$

The same formula is used for the ask side (see Beltran, Giot, and Grammig (2003) for a discussion of this measure of liquidity). By construction, the larger the transaction (i.e. the larger v), the larger the price paid as the market order hits more and more limit orders and is likely to walk up further in the book. We compute the price impacts for a volume v equal to 0.5, 1, 1.5 and 2 times a reference volume (the corresponding price impacts are labelled price impact level 1 to 4). The reference volume corresponds to a transaction for a nominal amount of 30,000 euros divided by the average price over the sample; this provides an easy comparison across stocks. Price impacts measure liquidity as offered by the book on an ex-ante basis, i.e before the transaction takes place. Trade aggressiveness measures how much traders use the book. It is computed as the volume-weighted average of the trades which are matched by standing limit orders strictly beyond the best quotes.[16] When trading volume rises, trade aggressiveness can remain low if the book provides more liquidity to the market (thus quoted depths rise).

As suggested by Figure 3, trading activity is highly concentrated in the afternoon trading session. This is consistent with the well-known influence of the pre-opening and opening of the US stock markets on the dynamics of the European markets. At the start of the trading session on Euronext, the volatility is particularly high (Figure 2), while the traded volume (Figure 3) or the average volume per trade (Figure 4) are not that large. On the other hand, traded volume increases at the end of the day while the increases in volatility appear more subdued. As far as the order book is concerned, it provides a reasonable amount of liquidity throughout the day. Although quoted spread and price impacts (see Figures 6, 9) are larger at the opening, they remain small and stable throughout the trading day, with a slight deterioration near the close of the trading session.[17] Depths at the quotes are up by roughly 50% in the afternoon compared with the morning (see Figure 8). Moreover and although trading volumes are larger after 2 pm, transaction costs, as measured by the effective spread (Figure 7), are quite low and constant, except at the start of the trading session where traders have to pay twice the price they pay during the rest of the day. Indeed, while trade aggressiveness appears to be large on average at the opening of the trading session and around the opening of the US markets, the provision of liquidity by limit orders in the book seems to avoid a sharp increase in transaction costs (except at the opening). These empirical facts are consistent with the previous findings reported in the literature (see Biais, Hillion, and Spatt (1995) for the Paris Bourse, Beltran, Giot, and Grammig (2003) for the Frankfurt XETRA platform, or Hamao and Hasbrouck (1995) for the Tokyo Stock Exchange). Note that for the whole sample, the average depth offered on the bid side is higher than on the ask side and, on average, the buy side of the order book seems to be more aggressive in price than the sell side. Nevertheless, these results may be only relevant for the time period considered in this study (as we ‘only’ deal with 5 months).

[16]For example, a buy trade must be matched with at least one standing limit order above the best ask price to be characterized as being ‘aggressive’.

[17]Note that the figures for the ask side of the book are very similar to those presented for the bid side. Hence they are not given here but are available on request.

B. The impact of volatility on liquidity measures

The main goal of the paper is to study how market conditions and liquidity are affected by volatility. As discussed above, what matters for market participants are deviations from expected volatility, hence the need to focus on the deseasonalized volatility and its impact on (deseasonalized) liquidity measures. While the raw data are first pre-sampled at the 15-minute frequency (to define the 15-minute returns and to compute the time-of-day patterns as given above for example), we thereafter focus on 4 sub-intervals which span one trading day: [9h:11h], [11h:13h], [13h:15h] and [15h:17h30]. The [9h:11h] interval is just after the market open, [11h:13h] ends with the traders' lunchtime, [13h:15h] ranges from the start of the afternoon trading up to the New York pre-open and [15h:17h30] should capture the increased activity due to the opening of the US markets and ends with the close of trading on the Euronext platform. Besides, the switch from 15-minute intervals to 2-hours intervals is consistent with the notion of realized volatility (see below) as a volatility measure computed from the 'aggregation' of really high-frequency squared returns. As such, estimation results (see the log-log regressions below) from models where the volatility is the independent variable should be less noisy. With respect to these 4 intervals, we thus compute the realized volatility, aggregated effective spread, aggregated quoted spread, aggregated traded volume, aggregated trade aggressiveness, aggregated ask and bid depths and different measures of the aggregated ask and bid price impacts (as defined above). We now proceed with the definition of these aggregated measures computed from the data sampled at the 15-minute frequency.

First and following Andersen and Bollerslev (1998) or Giot and Laurent (2004), we define the realized volatility as the sum of the intraday squared returns which pertain to the required intervals. As shown in Andersen and Bollerslev (1998), the realized volatility measure provides a model-free estimation of return volatility over a given time interval (provided that high-frequency returns are available). For example, with 15-minute returns and for the [11h-13h] time interval, the realized volatility on December 2, 2002 is computed as:

$$RV_{13h,2/12/02} = r^2_{11h15} + \ldots + r^2_{13h} \tag{3}$$

where r_{11h15} is the 15-minute return for the [11h-11h15] time interval and r_{13h} is the 15-minute return for the [12h45-13h] time interval on December 2, 2002. The aggregated effective spread, quoted spread, traded volume, trade aggressiveness, ask and bid depths and price impacts are respectively the mean effective spread, mean quoted spread, traded volume, mean trade aggressiveness, mean depths and mean price impacts (computed from the 15-minute intervals) averaged over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals.

In a second step and for each interval, the time-of-day pattern of each measure is computed (see above for the discussion of seasonality and the computation of the deseasonalized measures). Next we compute the deseasonalized variables by dividing each measure by its respective time-of-day. We then estimate the following log-log regressions:

$$ln(X_i) = \beta_0 + \beta_1 ln(RV_i) + \varepsilon_i, \qquad i = 1 \ldots N, \tag{4}$$

where X_i is successively S_i, Q_i, V_i, TA_i, DB_i, DA_i, BPI_i and API_i (respectively the deseasonalized aggregated effective spread, quoted spread, traded volume, trade aggressiveness, bid depth, ask depth, bid price impact and ask price impact), RV_i is the deseasonalized realized volatility and N is the total number of observations. Because we use log-log regressions, β_1 can be interpreted as an elasticity that 'links' deseasonalized variables. The interpretation of these elasticities is as follows. For the $ln(S_i) = \beta_0 + \beta_1 ln(RV_i) + \varepsilon_i$ regression for example, a β_1 of 0.3 would imply that a 100% increase in the level of realized volatility (with respect to its expected level based on the time-of-day) would yield a 30% increase in the effective spread (with respect to its expected level based on the time-of-day).

Estimation results for the six stocks are given in the top panel of Table II. Note that we also plot the relationship between the deseasonalized aggregated effective spread and the deseasonalized realized volatility in Figure 10 and the relationship between the deseasonalized aggregated trade aggressiveness and the deseasonalized realized volatility in Figure 11. The results indicate that the elasticity for the effective spread - realized volatility relationship is around 8% for Dexia, and a bit more than 20% for the other five stocks. For the trade aggressiveness - realized volatility relationship, the elasticities are around 15% for the three large-cap stocks, and range between 9% and 23% for the other three stocks. The figures also show that there is no sharp deterioration in market liquidity when volatility increases sharply. Indeed a positive relationship between both effective spread and trade aggressiveness vs realized volatility is at play (which is expected from the market microstructure literature), but this positive dependence is somewhat muted (see below for additional discussions). The analysis for the quoted spread and depths yields similar results. Table III shows that the elasticity for the quoted spread-realized volatility relationship is around 12% for Dexia, and between 22% and 28% for the other stocks. Furthermore, while there is a negative relationship between the depth (for both sides of the order book) and the realized volatility, it is not significant. We also look at the relationship between the deseasonalized aggregated price impact (level 1 to 4) and the deseasonalized realized volatility (this last analysis thus uses information provided by the full limit order book dataset). The outputs of the log-log regressions are given in Table IV and Table V. We can see that, for the elasticity between the bid price impact (for level 2, the reference volume of 30,000 euros) and the realized volatility, this relationship is slightly weaker for Dexia at 10% than for the other stocks (at more than 14%). Moreover, the numerical values are quite similar for the four price impact levels. For the sell side, results are roughly the same, as the elasticities remain below 10% (except for UCB and KBC, around 20%). These results are displayed graphically in Figures 12 and 13.

B.1. High and low volatility regimes

Up to now we analyzed the whole bunch of observations put together, i.e. we did not deal separately with high-volatility and low-volatility time periods. Thereafter we split the deseasonalized measures defined on the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals into a low-volatility and high-volatility subset. To construct the two sub-datasets, we apply a two-state Markov switching model (such as introduced by Hamilton, 1989) to the series of deseasonalized realized volatility. Using the smoothed transition probabilities, we can then immediately determine which observations belong to the low-volatility regime and which ones can be put into the high-volatility sub-dataset.

More formally, we assume that the deseasonalized realized volatility RV_i switches regime according to an unobserved variable s_i: regime 1 ($s_i = 1$) is the low-volatility state, while regime 2 ($s_i = 2$) is the high-volatility state. At time i, the volatility state is thus $s_i \in \{1, 2\}$ and the dynamics of s_i is governed by a Markov process: $P(s_i = 1|s_{i-1} = 1) = p_{11}$, $P(s_i = 2|s_{i-1} = 1) = 1 - p_{11}$, $P(s_i = 2|s_{i-1} = 2) = p_{22}$ and $P(s_i = 1|s_{i-1} = 2) = 1 - p_{22}$, where p_{11} (p_{22}) is the probability of being in the low-volatility (high-volatility) state at time i given that the low-volatility (high-volatility) state is observed at time $i-1$. In state m, the deseasonalized realized volatility is equal to μ_m, with variance σ_m^2. We estimate the parameters of the model using the MSVAR package (maximum likelihood, EM algorithm) of H.-M. Krolzig in the OX 3.2 econometric framework, which also computes the smoothed transition probabilities. Finally, these are used to separate the observations into the two sub-datasets. We then re-run the log-log regressions.

Estimation results for these regressions are given in the middle and bottom panels of Tables II, III, IV and V. Let us consider first the effective spread and trade aggressiveness. A comparison of the elasticities in both regimes indicates that the numerical values are close to one another for the effective spread, quite similar although sometimes different for the trade aggressiveness and very dissimilar for the traded volume. In all cases, the effective spread - realized volatility and trade aggressiveness - realized volatility elasticities do not significantly change when volatility switches from the low- to the high-volatility state.[18] In other words, these relationships (which focus mainly on the ex-post liquidity or actual cost of trading) do not seem to significantly deteriorate in times of high volatility. These results are corroborated by the estimates for the limit order book dataset (quoted spread, bid and ask depths, bid and ask price impacts), see the results given in Tables III, IV and V. As reported, most elasticities are not significant and only the quoted spread elasticity is significant during stress periods. This suggests that the Euronext system provides adequate liquidity in both low- and high-volatility regimes as the slopes of these key relationships do not change in a meaningful way (a trading system with poor liquidity would be characterized by increasing elasticities as volatility increases, indicating that liquidity dries up in high volatility regimes).

If high-volatility regimes do not significantly impact the elasticities of the effective spread - realized volatility and trade aggressiveness - realized volatility relationships, they do affect the *mean* (or expected value) of the effective spread and trade aggressiveness. These results, computed from a comparison of the figures given in the middle and bottom panels of Tables II, III, IV and V, are reported in Table VI. For UCB (the "worst case" in terms of deterioration of liquidity during the high-volatility regime), the effective spread goes up by 60% and trades are more aggressive (+9%) despite the decrease of liquidity in the book. Indeed, price impacts (bid side, level 3) surged by 39% on average, and quoted depths were 13% lower. This suggests that traders were somehow reluctant to enter large orders given the low liquidity offered by the book. Note that DEXIA is the most liquid stock as the effective spread only increases by 10%. Broadly speaking and looking at all reported results for the six stocks, the decrease in liquidity seems very reasonable when compared with the increase in average volatility between the low- and high-volatility regimes (nearly 500%). Moreover and given that the amount (in share volume) of the hidden orders (not featured in our database) on the Euronext trading platform is estimated at 30% of the total book (see D'Hondt, De Winne, and Francois-Heude (2002)), the argument according to which there is a sufficient liquidity provision seems to be valid.

[18]This was tested using regression analysis and appropriately defined dummy variables.

B.2. Additional results

For the aggregated effective spread and aggregated trade aggressiveness, we also re-estimate some of the log-log regressions allowing for a quadratic effect, i.e. we include the squared independent variable as an additional explicative variable. We thus estimate:

$$ln(S_i) = \beta_0 + \beta_1 ln(RV_i) + \beta_2 (ln(RV_i))^2 + \varepsilon_i, \tag{5}$$

and

$$ln(TA_i) = \beta_0 + \beta_1 ln(RV_i) + \beta_2 (ln(RV_i))^2 + \varepsilon_i \tag{6}$$

where the variables are defined as before. For the 6 stocks and for both liquidity measures, the β_2 coefficient is however not significant (full numerical results are available on request).

Finally, in a previous version of the paper, we also considered an exogenous volatility criteria: the low-volatility subset featured the measures for which the realized volatility was within one standard deviation of its expected value ('average volatility' group) while the high-volatility subset featured the intervals for which the realized volatility was beyond one standard deviation of its expected value ('above-average volatility' group). The estimation results were quite close to those shown above for the volatility criteria based on the Markov switching process and are therefore not included in this version of the paper.

V. Trading dynamics

In this section we analyze how the volatility level affects the interplay between the main liquidity components (spreads, price impacts, average volume per trade,...) and the relationships between liquidity and volatility. Because this analysis hinges on the investigation of the dynamics of liquidity, we use VAR models applied to the original data sampled at the 15-minute frequency. The VAR analysis will thus first be performed on the whole dataset, and then on the subsets defined by the low- and high-volatility states identified by the Markov switching model.[19]

[19] The use of VAR models to analyze high-frequency equidistantly time spaced data has been advocated by Joel Hasbrouck, see e.g. Hasbrouck (1999).

A. VAR models and impulse response functions

We model the dynamics between liquidity and volatility using a Vector Autoregression (VAR) model. VAR models are to some extent a-theoretical, in the sense that we do not really specify economic relationships. Hence, we need to impose some restrictions on the estimated coefficients to reconstruct the underlying structural model. We consider a VAR(p) model of the following type:

$$X_t = \Gamma_0 + \sum_{i=1}^{p} \Gamma_i X_{t-i} + \varepsilon_t \tag{7}$$

where X_t is the vector of endogenous variables and ε_t is the usual error term. With respect to the application considered in this paper, we estimate a 4-lag VAR (the lag dynamics is thus roughly equal to one hour as we work with 15-minute intervals), with 7 variables (6 of the 7 variables are endogenous and the last one is exogenous, see below). These variables, which have all been previously deseasonalized by their respective time-of-day as described in the preceding section, are:

- Liquidity ex-ante: quoted spread and the price impact for a trade of 45,000 euros (average of the ask and bid sides);
- Liquidity ex-post: effective spread and trade aggressiveness;
- Activity variables: number of trades and average volume per trade;
- Volatility.

We first test for block exogeneity of each of the variables and ascertain that only trade aggressiveness is exogenous at the 5% level. Thereafter, we thus estimate a VAR with 6 endogenous variables: quoted spread, average price impact for a transaction of 45,000 euros, number of trades, average volume per trade, the effective spread, and volatility; trade aggressiveness is the only exogenous variable. Using the BIC criteria, we further reduce the dimension of the system as it indicates that a 2-lag structure is adequate. Finally we estimate the selected VAR(2) model twice: first with the observations belonging to the low-volatility regime, and then with the observations which pertain to the high-volatility regime. Using a Cholesky decomposition, we further decompose the residuals ε_t to get a structural model:

$$X_t = \sum_{j=1}^{\infty} C_j e_{t-j} \tag{8}$$

This decomposition ensures that the individual shocks are orthogonal, i.e. that the variance-covariance matrix $V(e_t)$ is diagonal. It also allows the system analysis of the impact of a one-period shock to a given variable, also called impulse response functions. We compute the 20-lag (5 hours, about half a trading day) impulse response functions for the VAR model estimated first with all the data, and then with the data provided by the low- and high-volatility regime classification. For the first VAR(2) model as for the low- and high-volatility regime VAR(2) models, we tried several endogenous variable ordering to ascertain that the choice of ordering did not lead to different results. The impulse responses exhibit remarkably similar shapes whatever the ordering. This is important as it implies that the correlation between the individual shocks e_{jt} (where j denotes the j-th variable) is small and thus does not appear as important as in many macroeconomic structural models. The main argument as to why cross-correlations between shocks are large in macroeconomic models is that the data is typically monthly/quarterly and thus lagged response to a single shock within the month are aggregated and consequently treated as a contemporaneous impact when dealing with monthly data. This suggests that the chosen 15-minute interval is small enough to avoid aggregation issues.

Figures 14 to 25 report the impulse response for the 6 variables and for the 6 stocks in both regimes. We also compute 95% level confidence intervals, but do not report these in the paper. In both regimes, most of the impulse responses are significantly different from zero (flat IR), but there are no marked differences between the low- and high-volatility regimes (see below for additional discussion). Moreover, the confidence intervals for the high-volatility regime are larger than for the low-volatility regime; for many impulse responses, the confidence intervals for the low-volatility regime lie within the ones for the high-volatility regime.[20] In all cases the width of the confidence intervals strongly decreases after 4 periods on average, i.e. roughly one hour. Furthermore, for volatility shocks and the impulse responses of a variable to its own shock, impulse responses are significantly different between regimes at the 95% confidence level. To improve on the impulse response analysis, we compute two additional statistics: half-life times and cumulated impacts. The cumulated impact of a shock is defined as the sum of the impulse responses over all 20 periods; it is also the long-run impact of a permanent shock. The half-life is the time needed to achieve half of the cumulated impact; thus it measures the speed of return to equilibrium.

[20]The number of observations in the low-volatility regime is roughly twice the number of observations in the high-volatility regime.

B. Impulse response functions and the dynamics of liquidity

The impulse responses are reported in Figures 14 to 25. We summarize all results in Tables VII and VIII, which thus supplement/summarize the description given below.

A look at the impulse responses show that in both regimes, an increase in volatility decreases ex-ante and ex-post liquidity. Indeed, as the winner's curse rises with volatility, limit order traders want to be better rewarded for their provision of liquidity and consequently market orders become more expensive (see e.g. Foucault (1999)). This explains why, in both regimes, we find that liquidity drops when volatility surges. However we also find that, when faced with higher volatility, traders submit larger market orders despite higher potential trading costs. Traders also submit more frequent orders. If volatility is a proxy for the arrival of information, this is consistent with the the presence of informed traders keen on trading quickly.

For all variables, volatility shocks are significantly larger in the high-volatility regime. A one-standard-deviation volatility shock immediately increases the quoted spread by less than 16% in the low-volatility regime, and by 16% to 35% (depending on the stock) in the high-volatility regime. A similar result holds in the long run. Looking at the dynamics of the book depth, the contemporaneous effect of a volatility shock is positive in both regimes and larger during stress periods. Nevertheless, the long-term impact is smaller in the high-volatility regime for half of the stocks. Thus, we cannot conclude that book depth is significantly lower in the high-volatility regime. Regarding trading costs, the long-run impact of a volatility shock is 6% to 20% higher when volatility is high than when volatility is low. Finally, volatility shocks have a long-lasting impact on the liquidity measures. For example, after one hour, only half of the effect of the shock has been incorporated into liquidity. On the contrary, activity reacts within the first 15 minutes. Note also that the book reacts more rapidly (within 15 minutes) in the high-volatility regime. This is consistent with larger adverse selection risks and thus a more active monitoring of limit orders by traders. Overall, the impact of volatility on liquidity and trading costs is indeed more pronounced during stress periods, but the provision of liquidity does not really deteriorate either.

The analysis also shows that trading activity attracts the submission of aggressive limit orders (the spread decreases), whereas large trades deter them (larger spread). Besides, during the first hour after the shock, the surge in average volume attracts limit orders, but not at the best quotes: spreads rise, but the price impact is smaller. If there are more trades, the spread decreases while the book becomes thinner, which is the same result as in the long-run. Contrary to volatility shocks, liquidity reacts to an increase in activity quite quickly (15 minutes); this is likely due to competition in the provision of liquidity in non-informative periods.

When the quoted spread rises or the book becomes thinner, trading intensity and the average size of the trade drops. Interestingly, the impulse response of the average volume per trade to quoted spread shocks is (although negative) not significantly different from zero in both regimes. This may imply that the spread is not a key variable for the average volume per trade; depth seems more relevant for traders. Furthermore, the analysis highlights the fact that there is some kind of short-term trade-off in the provision of liquidity: a positive shock on the price impacts (lower depth) decreases contemporaneous spread, but increases it subsequently. Albeit not statistically significant, this effect is more pronounced when volatility is high.[21] In the long run, negative liquidity shocks lead to subsequent decreases in ex-ante and ex-post liquidity. This "vicious circle" seems to be more pronounced in the high-volatility regime (although the difference may not be statistically significant). For some stocks, the drop in liquidity (ex-ante and ex-post) is five times larger in the high-volatility regime. This shows that, in periods of turmoil, even without new information, liquidity can shrink when many traders withdraw from the exchange (liquidity shock). It is also worth stressing that a spread positive shock has a positive and significant impact on volatility.

Finally, for all stocks, the impulse responses of a variable to its own shock are always significantly lower in the low-volatility regime. Although shocks last for roughly the same time in both regimes, the impact on market conditions is thus much larger during turmoil. For instance, a negative shock to ex-ante liquidity when markets are volatile leads to a long-term decrease (in ex-ante liquidity) 20% to 80% larger than in normal periods. The good news (for the Euronext platform and for central banks) is however that, although shocks have larger impacts on average in high-volatility regimes, they are still absorbed quite rapidly as they last for about the same time in both regimes.

VI. Conclusion

Using limit order book and transaction data for three large-cap and three mid-cap Belgian stocks traded on the Euronext system, we study the relationships between different liquidity measures and market volatility. We consider ex-ante (e.g. quoted spread, bid and price price impacts, depths)

[21] We checked that this effect was not due to a particular ordering of the variables. Indeed, if we reorder the variables such that the spread causes the price impact (in the model presented, it is the opposite), we found exactly the same effect: a negative shock on the spread (smaller spread) increases contemporaneously price impacts (thinner book), but decreases it subsequently (the book fills up).

and ex-post (e.g. effective spread, trade aggressiveness) liquidity measures which are fully available once complete order book data is at hand. From an econometric point of view, we work with the realized volatility as popularized recently in Andersen and Bollerslev (1998), which allows us to define a low- and high-volatility regime based on Markov switching techniques, and with VAR models (à la Hasbrouck) that allow insight into the dynamical analysis of liquidity components. Thereafter, we thus assess the different relationships (mostly modelled as log-log regressions on appropriately defined liquidity measures) with all the data, and then separately in the low- and high-volatility regimes. This analysis thus sheds light on the behaviour of automated auction markets in times of low and high volatility, and allows us to quantify the impact of the switch in volatility regimes on key ex-ante and ex-post liquidity measures relevant for traders and/or institutional investors. In the last part of the paper, we model the trading dynamics using a VAR system (and impulse response analysis) applied to some market variables.

Our results indicate that the provision of liquidity in the Euronext trading system seems to be quite resilient to increases in volatility. Indeed, the slopes of these liquidity measures - volatility relationships (e.g. effective spread - volatility or trade aggressiveness - volatility relationships for example) do not significantly change when volatility switches from the low-volatility to the high-volatility regime. In contrast, the mean (or expected value) of each liquidity measure is usually significantly higher in the high-volatility state, but this was expected from the market microstructure literature. The dynamical analysis based on the VAR model presented in the second part of the paper does not allow us to be conclusive in either way (i.e. whether volatility seriously impacts liquidity, or that there is no impact). On the contrary, it offers a more balanced view according to which the volatility regime bears moderately on the dynamics of the liquidity provision. As such, the main empirical result of this study is that there is no real important deterioration in the provision of liquidity when volatility increases, although we do find that it is more costly to trade when volatility is high and that the market dynamics is somewhat affected.

As indicated by many theoretical studies, adverse selection increases when volatility increases, which results in a more costly provision of limit orders. As a consequence, market liquidity drops when volatility increases. In periods of financial distress, this is the one of the main concerns of central banks since this behavior may lead to the collapse or near-collapse of financial markets (e.g. the 1987 krach and the LTCM failure in 1998, among others). As recently suggested by Mishkin and White (2002), a financial crisis combined with a large drop in liquidity may be particularly destabilizing, and thus potentially requires prompt and adequate action by monetary authorities.

The concern about a systemic drop in financial liquidity, shared by many studies (see e.g. Borio and Lowe (2002) and Borio (2003)), leads many academics and practitioners to suggest that central banks should perhaps play a regulatory role in financial markets. However and given the many ways stock markets can be set up (pure order book market, price-driven market, hybrid market), the first natural step is to understand the dynamics of liquidity in stress periods in each type of market. While this kind of study had already been done for some price-driven markets or for some hybrid markets, no empirical study had yet focused on that topic for Euronext. Regarding the behavior of liquidity in high-volatility regimes, the results presented in this paper are particularly promising. Indeed, even if trading costs are larger in stress periods, the trading system does not seem to break down.

Our results of course pave the way for additional research linked to that topic. An obvious extension would be to assess our relationships on an extended dataset which would feature a much larger number of stocks sub-divided into smaller groups based on the firms' characteristics. In this extended setting, we could thus quantify the possible deterioration in the provision of liquidity according to the most salient characteristics of the stock (e.g. small-cap, mid-cap, large-cap; type of industry;...). It could also be argued that the Markov switching algorithm should be applied to the overall market volatility (for example the volatility of the index). This would lead to the same classification of low- and high-volatility regimes for all stocks. In the same vein, the classification into low- and high-regimes could also be done with respect to the trading activity for example (instead of volatility). This would yield insights into the provision of liquidity in different trading environments.

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Table I
Descriptive statistics.

	DEXIA	ELECTRABEL	INTERBREW	KBC	SOLVAY	UCB
Market capitalization	17.44	13.54	9.27	12.76	5.66	4.53
Average price	10.01	228.29	18.94	29.39	59.56	24.72
Average volume per trade	1695.18	159.67	1048.36	502.10	302.63	524.51
Average number of transactions per day	719.42	329.25	411.34	354.37	261.73	275.61
% of aggressive trades	16.32	20.10	22.27	24.31	21.40	25.46
% of volume traded for a client account	57.74	70.30	77.36	71.95	70.66	74.1
% of volume traded for a proprietary account	42.17	29.65	22.58	27.94	29.25	25.86
% of volume traded on a market maker account	0.09	0.04	0.06	0.12	0.10	0.04
% of transactions with unknown sign	0.83	0.67	0.64	0.79	0.43	0.72
% of inconsistencies (LOB vs trades datasets)	1.79	1.14	1.32	1.44	0.91	1.21

Descriptive statistics for the 6 Brussels traded stocks selected in the empirical analysis. An aggressive trade is defined as a trade which is matched with standing limit orders beyond the best quote. Market caps are expressed in billions of euros.

Table II

Descriptive statistics and elasticities (I).

All observations							
	N	Effective spread		Traded volume		Trade aggressiveness	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	409	0.081 (0)		0.152 (0)		0.148 (0)	
ELECTRABEL	409	0.248 (0)		0.159 (0)		0.167 (0)	
INTERBREW	409	0.215 (0)		0.131 (0)		0.130 (0)	
KBC	409	0.241 (0)		0.045 (0.16)		0.109 (0)	
SOLVAY	409	0.235 (0)		0.117 (0)		0.227 (0)	
UCB	409	0.255 (0)		0.055 (0.08)		0.089 (0)	
Low-volatility regime							
	N	Effective spread		Traded volume		Trade aggressiveness	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	335	0.092 (0)	0.982	0.110 (0)	0.949	0.183 (0)	0.980
ELECTRABEL	358	0.246 (0)	0.933	0.111 (0)	0.926	0.174 (0)	0.973
INTERBREW	245	0.202 (0)	0.856	0.081 (0.09)	0.879	0.140 (0.03)	0.919
KBC	293	0.237 (0)	0.898	0.025 (0.59)	0.986	0.151 (0)	0.973
SOLVAY	267	0.224 (0)	0.844	0.161 (0)	0.961	0.206 (0)	0.902
UCB	324	0.270 (0)	0.889	0.043 (0.27)	0.957	0.116 (0.01)	0.981
High-volatility regime							
	N	Effective spread		Traded volume		Trade aggressiveness	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	74	0.073 (0.14)	1.083 (0)	0.418 (0)	1.230 (0)	0.251 (0.01)	1.089 (0.07)
ELECTRABEL	51	0.307 (0)	1.469 (0)	0.491 (0.01)	1.516 (0)	0.295 (0.29)	1.189 (0.01)
INTERBREW	164	0.198 (0)	1.215 (0)	0.229 (0.09)	1.181 (0)	-0.015 (0.85)	1.121 (0)
KBC	116	0.274 (0)	1.259 (0)	0.382 (0.01)	1.035 (0.51)	0.121 (0.41)	1.068 (0.06)
SOLVAY	142	0.239 (0)	1.294 (0)	0.124 (0.22)	1.074 (0.09)	0.186 (0.04)	1.184 (0)
UCB	85	0.208 (0.01)	1.422 (0)	0.293 (0.10)	1.162 (0.05)	0.146 (0.27)	1.072 (0.12)

Descriptive statistics and outputs of the log-log regressions where the dependent variable is successively the aggregated effective spread, the aggregated traded volume and the aggregated trade aggressiveness, the independent variable is the realized volatility in all cases. All measures are computed over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals and are deseasonalized (by their respective time-of-day) prior to running the regressions. The panel 'Low-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the low-volatility regime; the panel 'High-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the high-volatility regime. 'Mean' is the mean of the dependent variable and 'elasticity' is the regression coefficient. For the 'elasticity' column, heteroscedastic-consistent P-values for the null hypothesis that the coefficient is significant are provided in parenthesis; for the 'mean' column, we provide the P-value for the equality test across both panels. The time period is December 2, 2002 to April 30, 2003.

Table III
Descriptive statistics and elasticities (II).

All observations							
	N	Quoted spread		Bid depth (euros)		Ask depth (euros)	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	409	0.118 (0)		-0.065 (0.03)		-0.063 (0.03)	
ELECTRABEL	409	0.266 (0)		-0.009 (0.81)		-0.025 (0.51)	
INTERBREW	409	0.218 (0)		-0.002 (1)		-0.014 (0.64)	
KBC	409	0.246 (0)		0.018 (0.62)		0.004 (0.91)	
SOLVAY	409	0.229 (0)		0.009(0.79)		0.007 (0.84)	
UCB	409	0.287 (0)		-0.024 (0.48)		-0.043 (0.20)	
Low-volatility regime							
	N	Quoted spread		Bid depth (euros)		Ask depth (euros)	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	335	0.130 (0)	0.970	-0.090 (0.04)	1.022	-0.084 (0.05)	1.021
ELECTRABEL	358	0.262 (0)	0.926	-0.016 (0.66)	0.984	-0.031 (0.40)	0.988
INTERBREW	245	0.207 (0)	0.857	0 (1)	0.992	-0.013 (0.80)	0.997
KBC	293	0.253 (0)	0.898	-0.084 (0.13)	0.977	-0.089 (0.11)	0.985
SOLVAY	267	0.218 (0)	0.845	0.020 (0.71)	1.005	0.008 (0.88)	1.015
UCB	324	0.295 (0)	0.869	-0.003 (0.95)	1.028	-0.016 (0.74)	1.039
High-volatility regime							
	N	Quoted spread		Bid depth (euros)		Ask depth (euros)	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	74	0.170 (0)	1.135	0.108 (0.42)	0.898	0.077 (0.56)	0.906
ELECTRABEL	51	0.353 (0)	1.525	-0.250 (0.47)	1.115	-0.254 (0.46)	1.082
INTERBREW	164	0.200 (0)	1.213	0.077 (0.55)	1.012	0.031 (0.81)	1.004
KBC	116	0.194 (0.02)	1.258	0.265 (0.10)	1.058	0.225 (0.16)	1.038
SOLVAY	142	0.189 (0.01)	1.291	-0.126 (0.31)	0.990	-0.154 (0.20)	0.972
UCB	85	0.189 (0.02)	1.498	-0.137 (0.41)	0.893	-0.149 (0.39)	0.852

Descriptive statistics and outputs of the log-log regressions where the dependent variable is successively the aggregated quoted spread, the aggregated bid depth (in euros) and the aggregated ask depth (in euros), the independent variable is the realized volatility in all cases (and a constant). All measures are computed over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals and are deseasonalized (by their respective time-of-day) prior to running the regressions. The panel 'Low-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the low-volatility regime; the panel 'High-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the high-volatility regime. 'Mean' is the mean of the dependent variable and 'elasticity' is the regression coefficient. For the 'elasticity' column, heteroscedastic-consistent P-values for the null hypothesis that the coefficient is significant are provided in parenthesis; for the 'mean' column, we provide the P-value for the equality test across both panels. The time period is December 2, 2002 to April 30, 2003.

Table IV
Descriptive statistics and elasticities (III).

	N	Bid PI1 Elasticity	Bid PI1 Mean	Bid PI2 Elasticity	Bid PI2 Mean	Bid PI3 Elasticity	Bid PI3 Mean	Bid PI4 Elasticity	Bid PI4 Mean
All observations									
DEXIA	404	0.059 (0.43)		0.100 (0)		0.096 (0)		0.096 (0)	
ELECTRABEL	363	0.170 (0)		0.186 (0)		0.181 (0)		0.203 (0)	
INTERBREW	398	0.134 (0)		0.146 (0)		0.136 (0)		0.132 (0.03)	
KBC	405	0.126 (0.01)		0.141 (0)		0.154 (0)		0.153 (0)	
SOLVAY	391	0.231 (0)		0.239 (0)		0.231 (0)		0.228 (0)	
UCB	408	0.146 (0)		0.142 (0)		0.148 (0)		0.152 (0)	
Low-volatility regime									
DEXIA	332	0.115 (0.18)	0.993	0.166 (0)	0.990	0.149 (0)	0.985	0.135 (0)	0.981
ELECTRABEL	314	0.166 (0.03)	0.952	0.167 (0.01)	0.943	0.193 (0)	0.939	0.218 (0)	0.941
INTERBREW	238	0.116 (0.17)	0.917	0.154 (0.04)	0.905	0.139 (0.03)	0.908	0.136 (0.03)	0.915
KBC	289	0.100 (0.22)	0.923	0.135 (0.01)	0.931	0.139 (0)	0.930	0.130 (0)	0.929
SOLVAY	252	0.247 (0.02)	0.895	0.220 (0)	0.882	0.221 (0)	0.880	0.204 (0)	0.881
UCB	323	0.143 (0.02)	0.913	0.118 (0.01)	0.921	0.126 (0)	0.926	0.132 (0)	0.929
High-volatility regime									
DEXIA	72	-0.778(0.29)	1.030	-0.077 (0.70)	1.046	-0.086 (0.65)	1.070	0.066 (0.69)	1.087
ELECTRABEL	49	0.478 (0.14)	1.336	-0.139 (0.76)	1.398	-0.580 (0.23)	1.430	-0.365 (0.28)	1.416
INTERBREW	160	0.113 (0.46)	1.123	0.084 (0.55)	1.141	0.050 (0.67)	1.137	0.052 (0.61)	1.127
KBC	116	0.183 (0.38)	1.195	0.216 (0.15)	1.175	0.218 (0.11)	1.178	0.176 (0.15)	1.178
SOLVAY	139	0.092 (0.60)	1.197	0.262 (0.05)	1.221	0.247 (0.03)	1.226	0.246 (0.02)	1.224
UCB	85	0.257 (0.25)	1.330	0.246 (0.14)	1.302	0.189 (0.14)	1.283	0.180 (0.10)	1.272

Descriptive statistics and outputs of the log-log regressions where the dependent variable is successively the bid price impacts from level 1 to 4, the independent variable is the realized volatility in all cases (and a constant). All measures are computed over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals and are deseasonalized (by their respective time-of-day) prior to running the regressions. The panel 'Low-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the low-volatility regime; the panel 'High-volatility regime' gives the outputs for the sub-datasets where the realized volatility is in the high-volatility regime. 'Mean' is the mean of the dependent variable and 'elasticity' is the regression coefficient. For the 'elasticity' column, heteroscedastic-consistent P-values for the null hypothesis that the coefficient is significant are provided in parenthesis; for the 'mean' column, we provide the P-value for the equality test across both panels. The time period is December 2, 2002 to April 30, 2003.

Table V
Descriptive statistics and elasticities (IV).

All observations									
	N	Ask PI1		Ask PI2		Ask PI3		Ask PI4	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	403	0.094 (0.03)		0.089 (0.01)		0.087 (0)		0.088 (0)	
ELECTRABEL	350	0.098 (0.13)		0.083 (0.08)		0.110 (0.01)		0.091 (0.03)	
INTERBREW	397	0.107 (0.03)		0.098 (0.01)		0.090 (0.01)		0.083 (0.01)	
KBC	407	0.218 (0)		0.213 (0)		0.211 (0)		0.211 (0)	
SOLVAY	397	0.048 (0.36)		0.092 (0.03)		0.116 (0)		0.125 (0)	
UCB	407	0.188 (0)		0.193 (0)		0.191 (0)		0.176 (0)	
Low-volatility regime									
	N	Ask PI1		Ask PI2		Ask PI3		Ask PI4	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	329	0.083 (0.16)	0.976	0.085 (0.06)	0.975	0.092 (0.02)	0.974	0.096 (0.01)	0.975
ELECTRABEL	303	0.062 (0.42)	0.903	0.036 (0.53)	0.917	0.056 (0.27)	0.923	0.054 (0.25)	0.928
INTERBREW	239	0.081 (0.29)	0.910	0.062 (0.38)	0.918	0.040 (0.51)	0.918	0.048 (0.38)	0.923
KBC	293	0.236 (0)	0.914	0.231 (0)	0.912	0.217 (0)	0.916	0.217 (0)	0.917
SOLVAY	259	-0.046 (0.59)	0.941	-0.008 (0.91)	0.916	0.032 (0.57)	0.907	0.053 (0.31)	0.904
UCB	322	0.148 (0.01)	0.905	0.191 (0)	0.917	0.185 (0)	0.924	0.172 (0)	0.934
High-volatility regime									
	N	Ask PI1		Ask PI2		Ask PI3		Ask PI4	
		Elasticity	Mean	Elasticity	Mean	Elasticity	Mean	Elasticity	Mean
DEXIA	74	0.251 (0.17)	1.107	0.122 (0.37)	1.113	0.107 (0.34)	1.118	0.101 (0.29)	1.114
ELECTRABEL	47	-0.110 (0.84)	1.683	-0.119 (0.70)	1.582	-0.079 (0.74)	1.543	-0.052 (0.81)	1.502
INTERBREW	158	-0.084 (0.69)	1.134	0.054 (0.70)	1.122	0.068 (0.58)	1.122	0.034 (0.74)	1.115
KBC	114	0.082 (0.79)	1.218	0.140 (0.47)	1.222	0.078 (0.61)	1.211	0.080 (0.54)	1.210
SOLVAY	138	0.397 (0.02)	1.111	0.397 (0)	1.159	0.311 (0)	1.175	0.260 (0)	1.180
UCB	85	-0.114 (0.55)	1.361	-0.082 (0.60)	1.317	0.044 (0.72)	1.289	0.086 (0.44)	1.251

Descriptive statistics and outputs of the log-log regressions where the dependent variable is successively the ask price impacts from level 1 to 4, the independent variable is the realized volatility in all cases (and a constant). All measures are computed over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals and are deseasonalized (by their respective time-of-day) prior to running the regressions. The panel ‘Low-volatility regime’ gives the outputs for the sub-datasets where the realized volatility is in the low-volatility regime; the panel ‘High-volatility regime’ gives the outputs for the sub-datasets where the realized volatility is in the high-volatility regime. ‘Mean’ is the mean of the dependent variable and ‘elasticity’ is the regression coefficient. For the ‘elasticity’ column, heteroscedastic-consistent P-values for the null hypothesis that the coefficient is significant are provided in parenthesis; for the ‘mean’ column, we provide the P-value for the equality test across both panels. The time period is December 2, 2002 to April 30, 2003.

Table VI
% change in the mean of each liquidity variable when switching from the low- to the high-volatility regime.

	% of limit orders	Effective spread	Traded volume	Trade aggressiveness	Quoted spread	BID			ASK		
						Depth	PI1	PI3	Depth	PI1	PI3
DEXIA	9%	10%	30%	11%	17%	-12%	4%	9%	-11%	13%	15%
ELECTRABEL	1%	57%	64%	22%	65%	13%	40%	52%	10%	86%	67%
INTERBREW	4%	42%	34%	22%	42%	2%	22%	25%	1%	25%	22%
KBC	6%	40%	5%	10%	40%	8%	29%	27%	5%	33%	32%
SOLVAY	9%	53%	12%	31%	53%	-1%	34%	39%	-4%	18%	30%
UCB	9%	60%	21%	9%	72%	-13%	46%	39%	-18%	50%	40%

The table reports the % change in the mean of each liquidity variable when switching from the low- to the high-volatility regime. Depth corresponds to the depth at the best prices. PI1 and PI3 correspond to the price impacts computed for a transaction of 15,000 and 45,000 euros respectively. The null hypothesis of the equality in means is rejected at the 5% level for all variables.

Table VII
The dynamics of liquidity.

shock	volatility		av. volu		nb tr		pi3		qsp		sp	
	L	H	L	H	L	H	L	H	L	H	L	H
volatility	+	+							+	+		
av. volu	+	+	+	+			-	-				
nb tr	+	+			+	+		-	-	-		
pi3	+	+	-				+	+	+			
qsp	+	+		+	-	-	-+	-+	+	+	+	+
sp	+	+	+	+	-	-			+	+	+	+

This table presents a summary of the VAR results (analysis of the dynamics of liquidity). A "+" ("-") means that the shock on the given variable (in the top row) has a positive (negative) and significant impact on the variable (in the first column). In a few cases, we report a "-+", which indicates that the shock is first negative and then positive. "H" refers to the high-volatility state, while "L" refers to the low-volatility state. Note that av. volu relates to the average volume per trade, nb tr, the number of trades, pi3, the level 3 price impact, qsp, the quoted spread, sp, the effective spread.

Table VIII
Half-life of the impulse responses.

shock	volatility	av. volu	nb tr	pi3	qsp	sp
volatility	15				30 (15 mn)	
av. volu	15	1H		15		
nb tr	15		15	15	15	
pi3	1H (15 mn)	15		30 (15 mn)	1H30	
qsp	1H	15	15	1H	15	30
sp	1H	15	15		45	15

This table reports the half-life of the impulse responses. All results are expressed in minutes except when there is an "H" (for hour). We only report results for the significant impulse responses. All results are for the low- and high-volatility states, except when there is a number in parenthesis (high-volatility state). Note that av. volu relates to the average volume per trade, nb tr, the number of trades, pi3, the level 3 price impact, qsp, the quoted spread, sp, the effective spread.

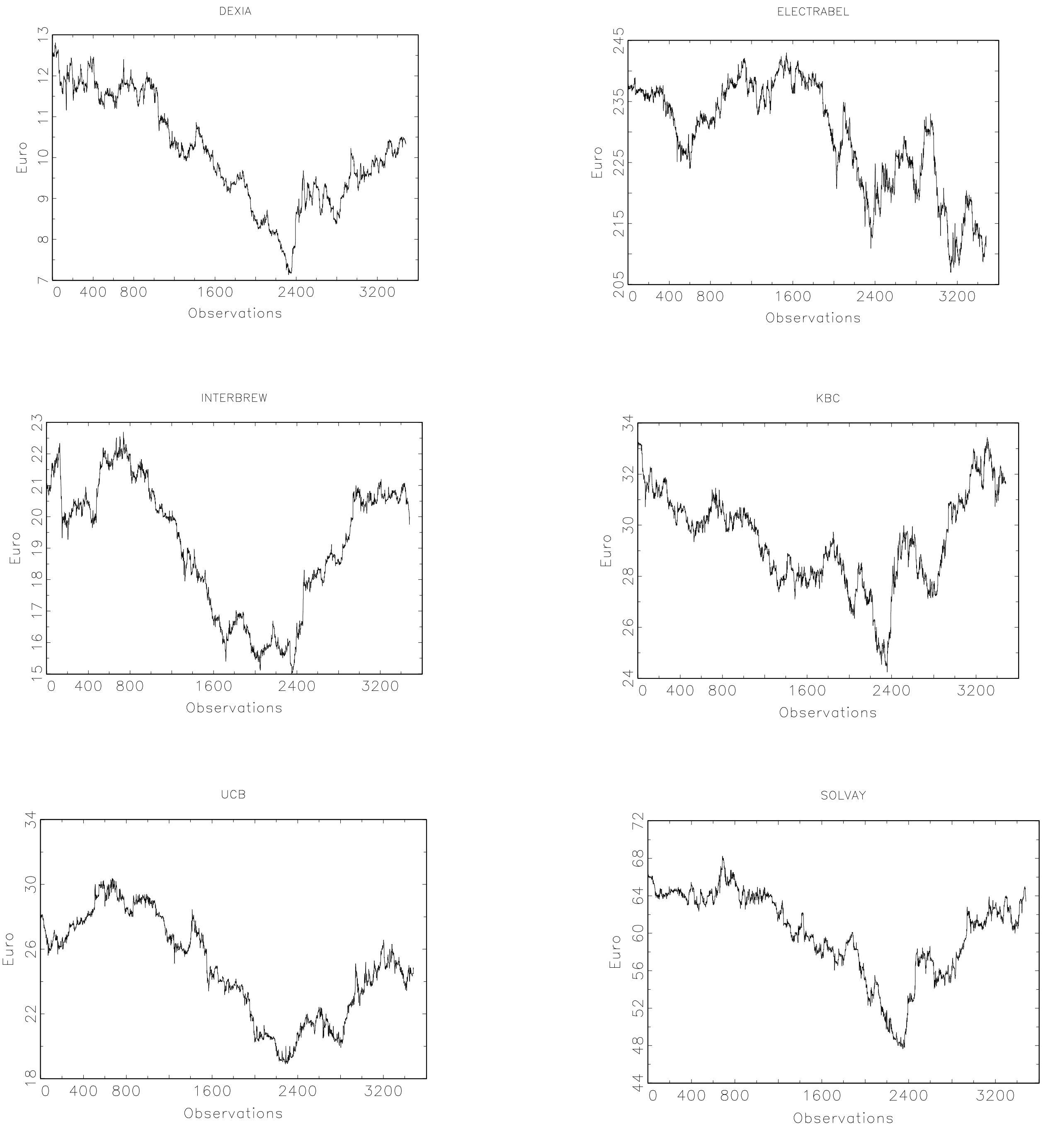

Figure 1. Stock prices. This figure shows the pattern of the stock prices (sampled at 15-minute intervals) over our sample. The time period is December 2, 2002 to April 30, 2003

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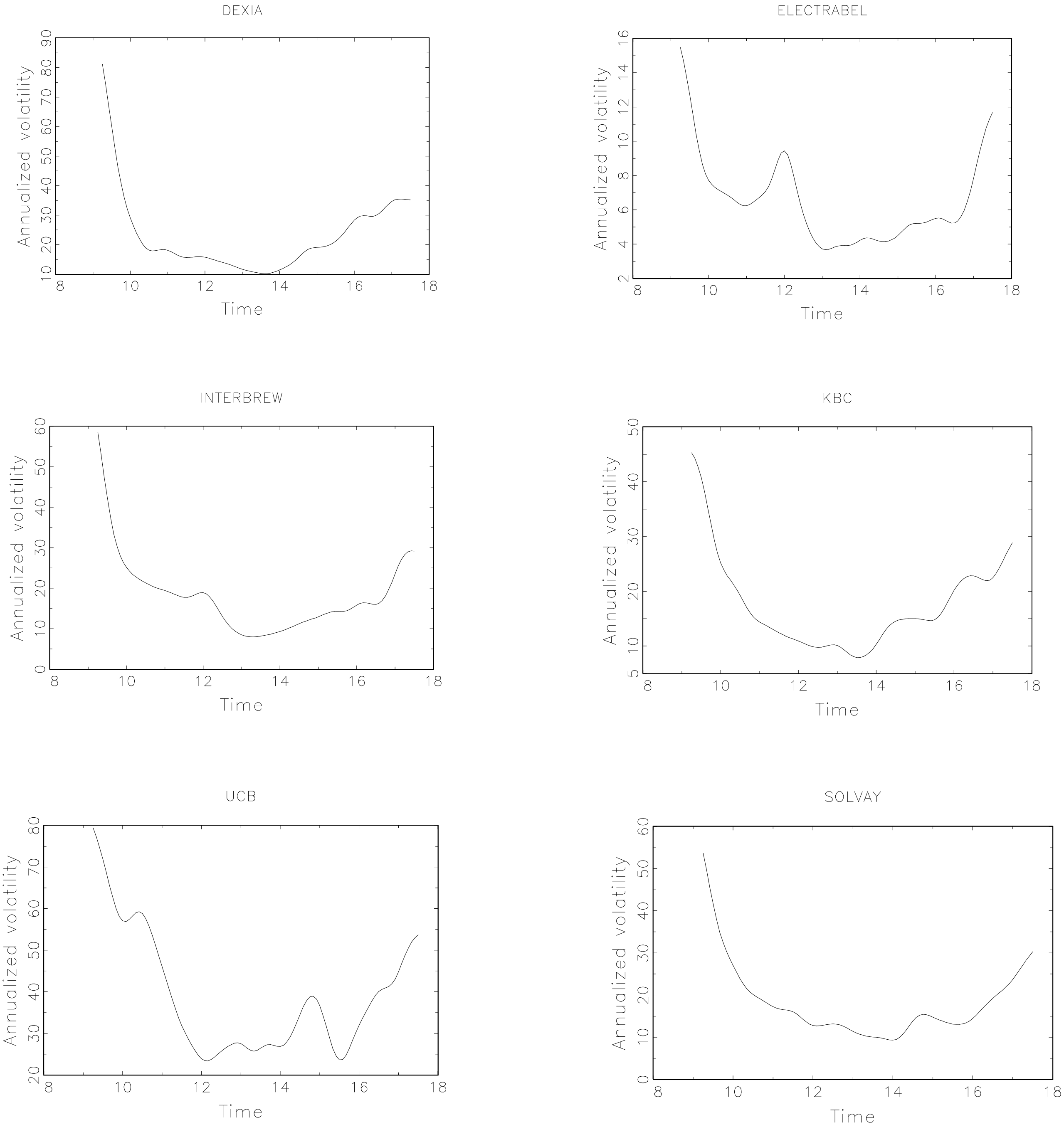

Figure 2. Time-of-day for the volatility. This figure shows the time-of-day pattern for the 15-minute return volatility (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

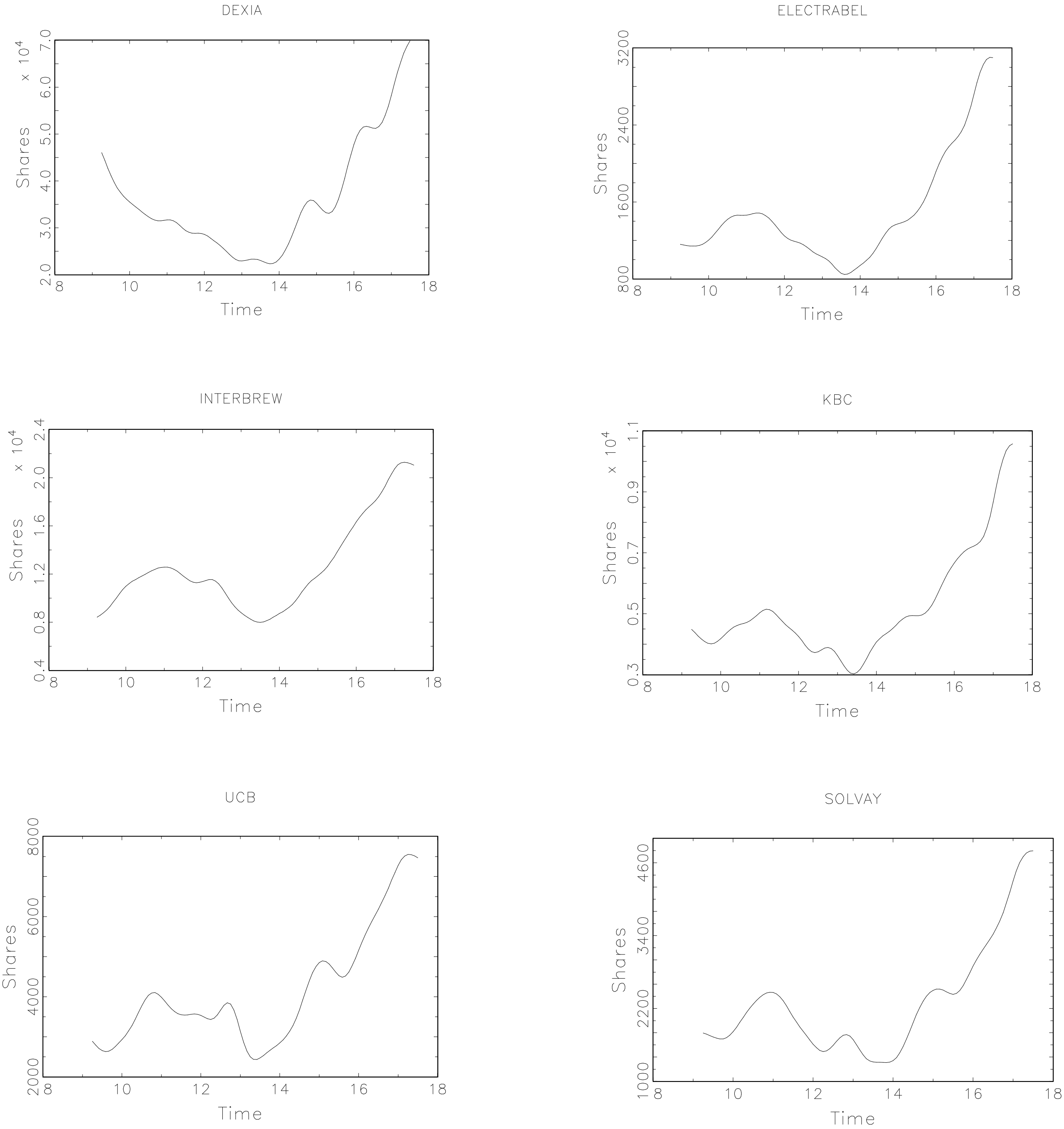

Figure 3. Time-of-day for the traded volume. This figure shows the time-of-day pattern for the 15-minute traded volume (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

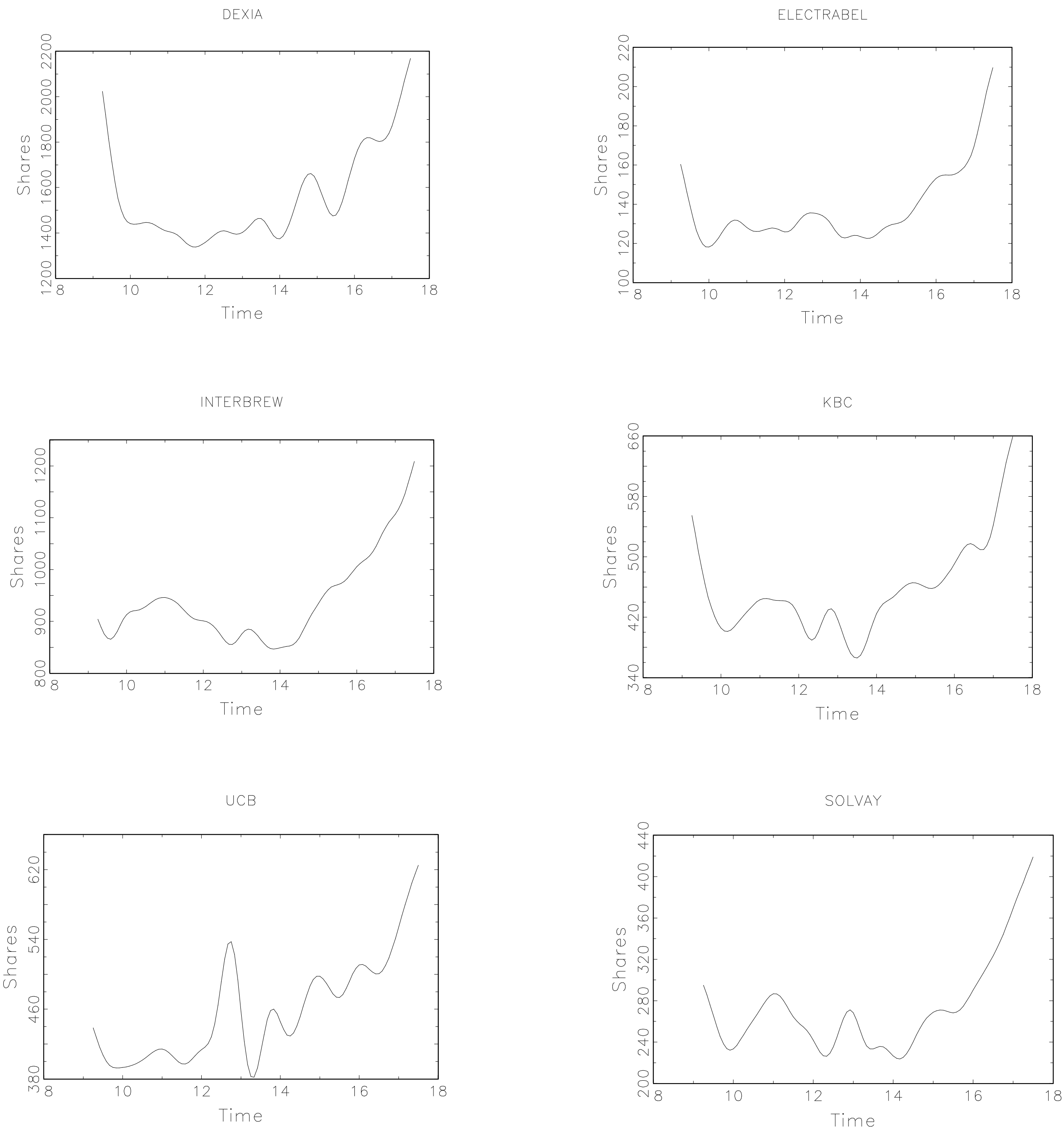

Figure 4. Time-of-day for the average volume per trade. This figure shows the time-of-day pattern for the average volume per trade (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

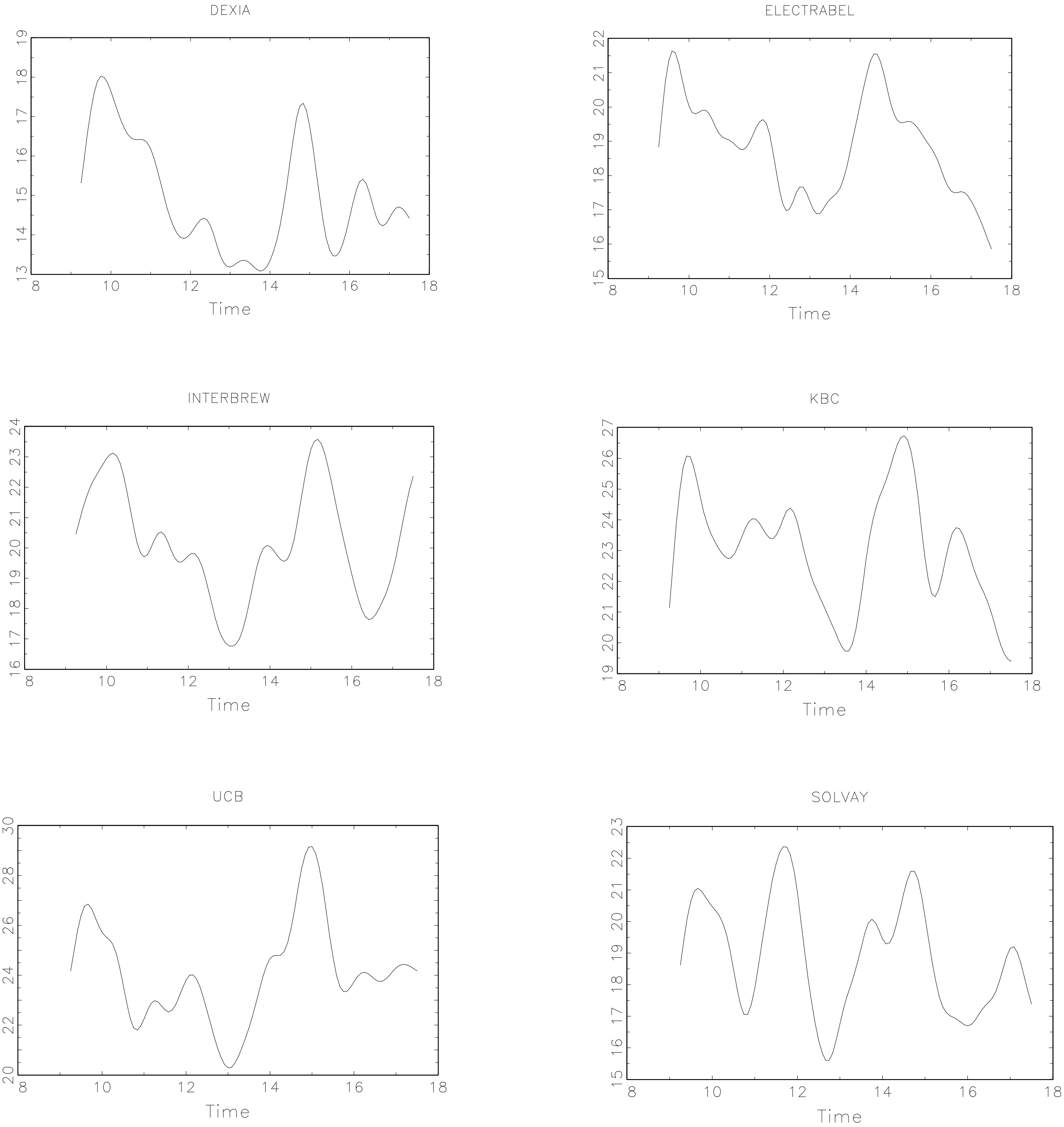

Figure 5. Time-of-day for the trade aggressiveness. This figure shows the time-of-day pattern for the trade aggressiveness (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

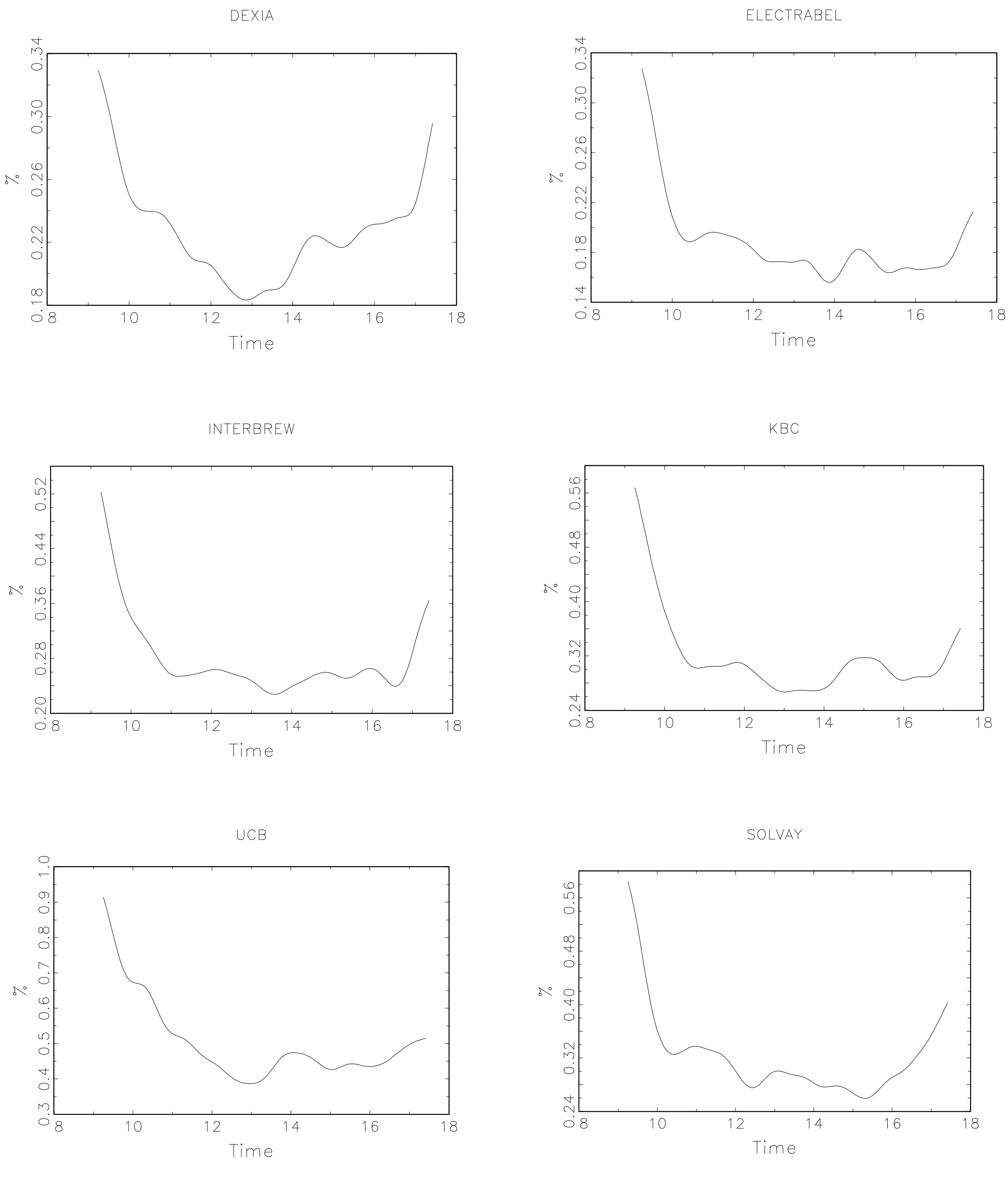

Figure 6. Time-of-day for the relative inside spread. This figure shows the time-of-day pattern for the relative inside spread (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

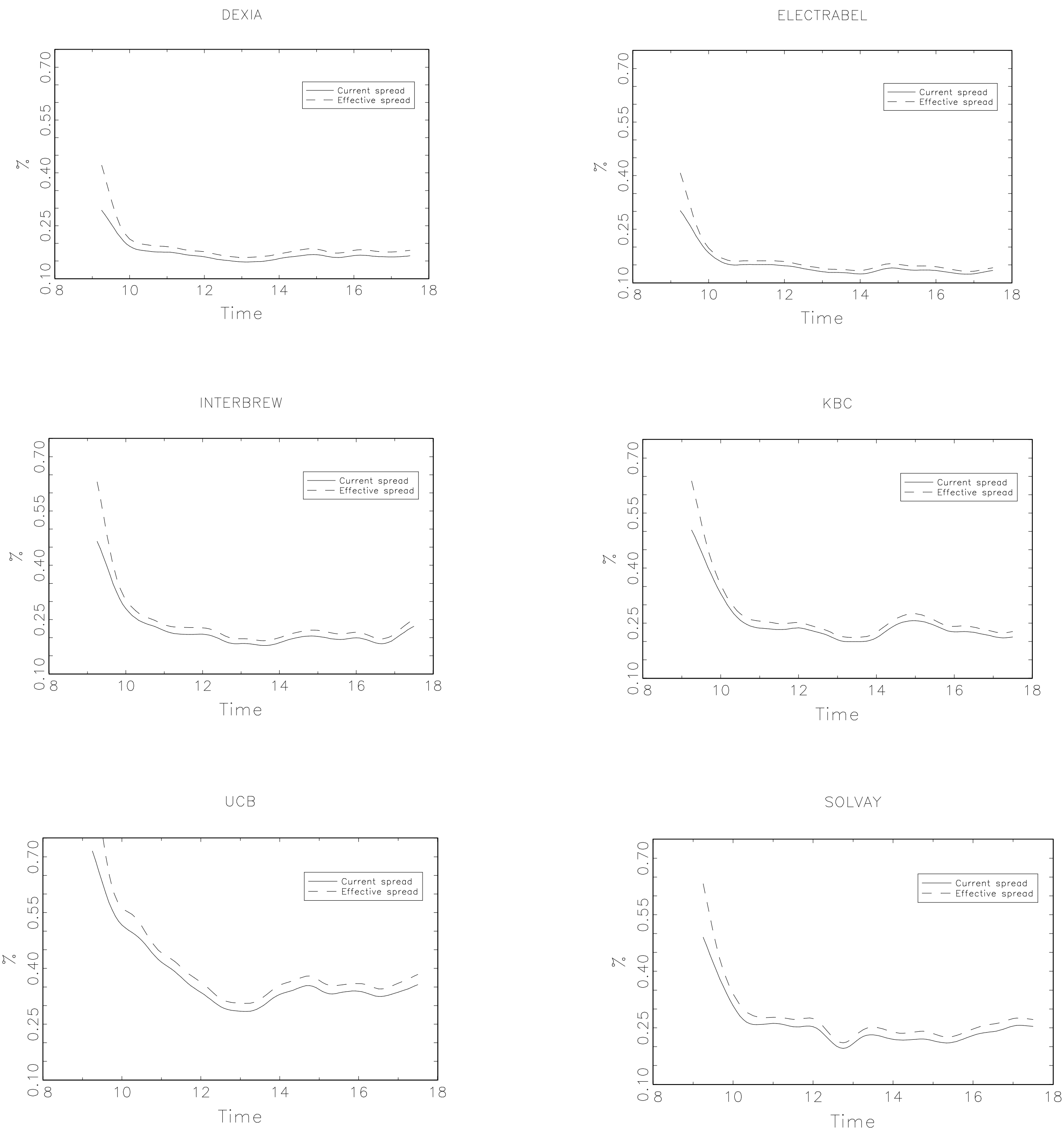

Figure 7. Time-of-day for the current and effective spread. This figure shows the time-of-day pattern for the current and effective spread (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

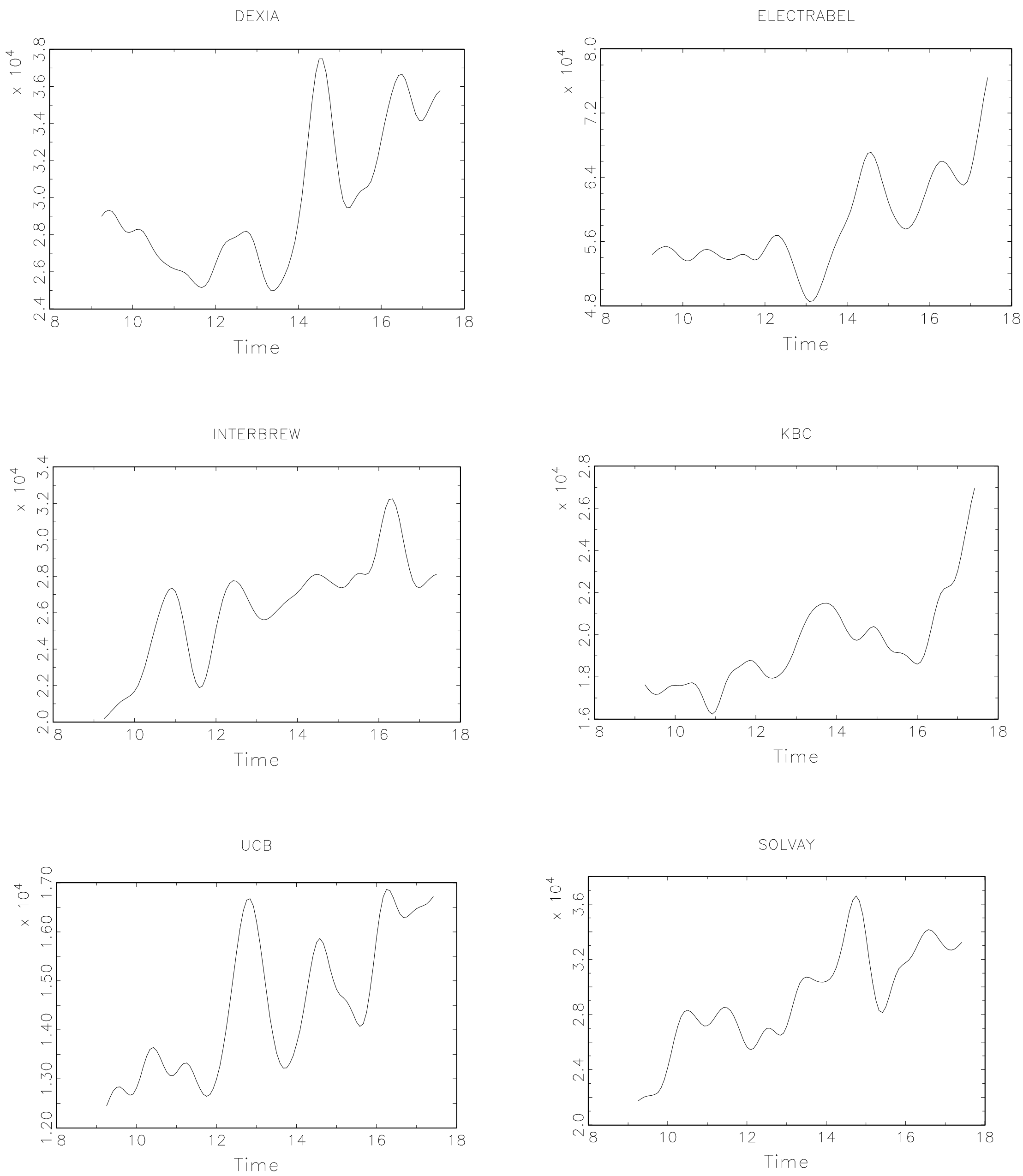

Figure 8. Time-of-day for the inside bid depth (in euros). This figure shows the time-of-day pattern for the inside bid depth (in euros) (smoothed using the Nadaraya-Watson estimator). The time period is December 2, 2002 to April 30, 2003.

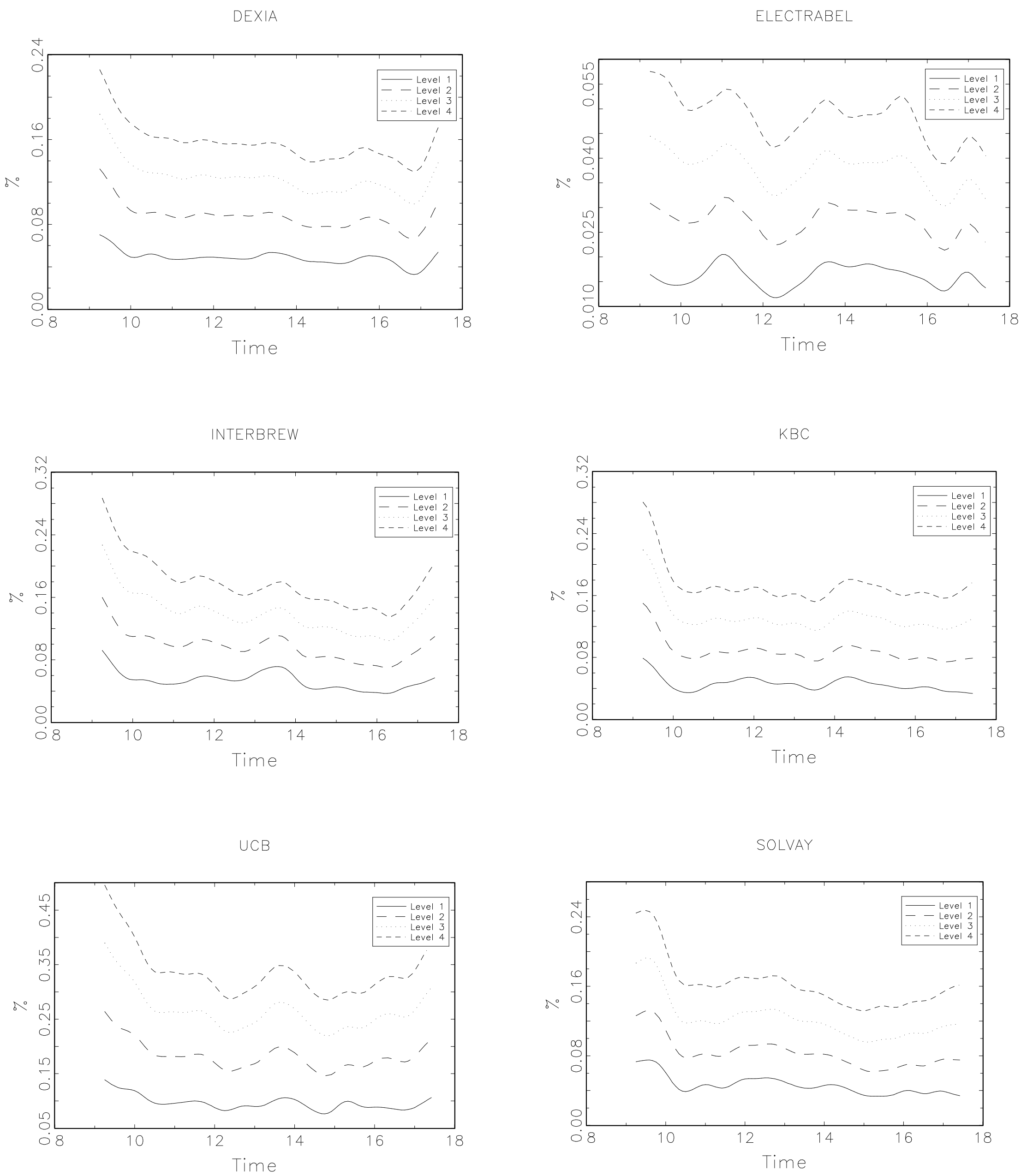

Figure 9. Time-of-day for the bid price impacts. This figure shows the time-of-day pattern for the bid price impacts (smoothed using the Nadaraya-Watson estimator). Price impacts are computed for volumes of 0.5, 1, 1.5 and 2 times the reference volume, which is computed as the volume corresponding to a transaction of 30,000 euros at the average price for the stock over the sample. The time period is December 2, 2002 to April 30, 2003.

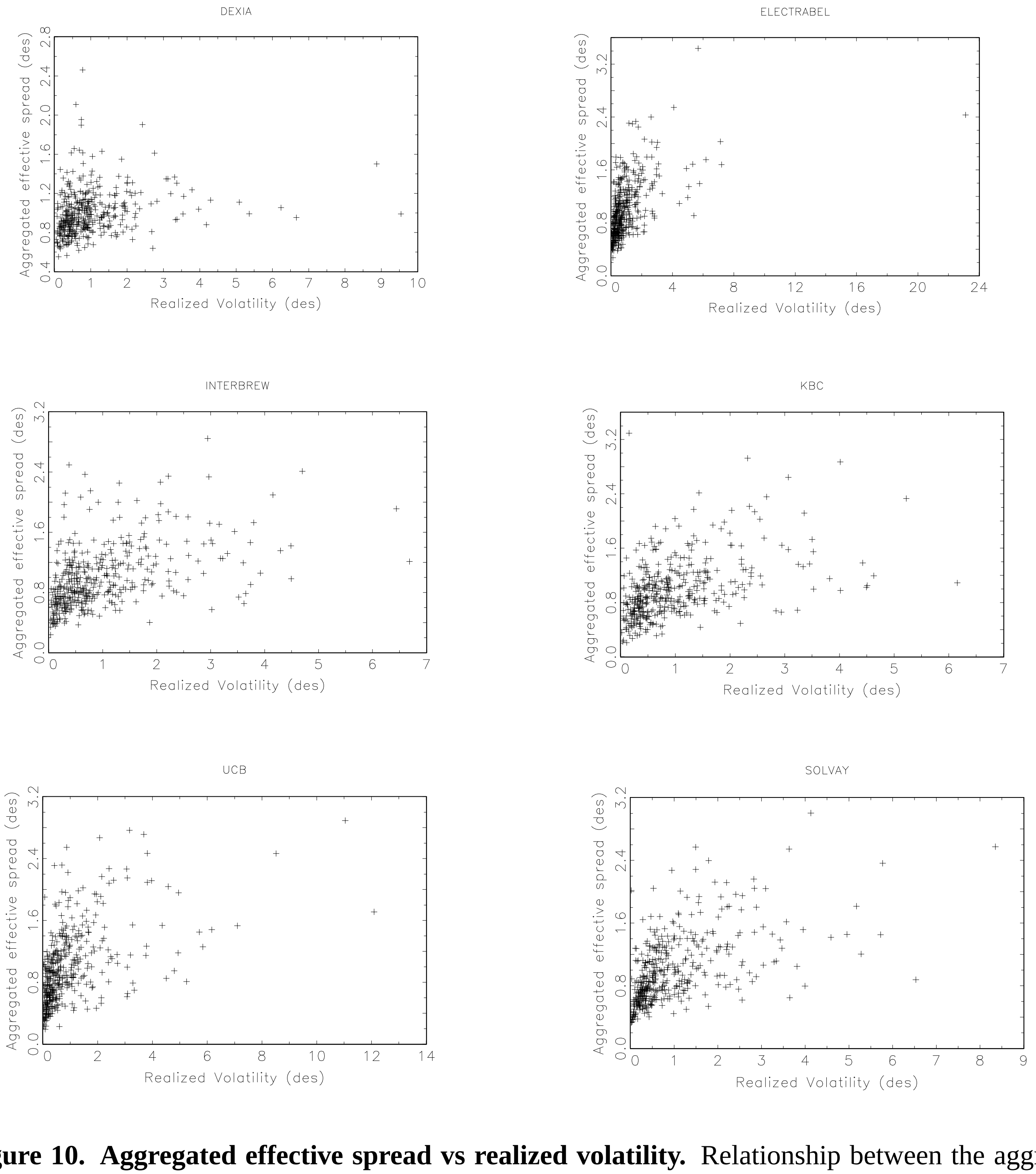

Figure 10. Aggregated effective spread vs realized volatility. Relationship between the aggregated effective spread and the realized volatility. The aggregated effective spread is the average effective spread over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals; the realized volatility is defined over the same intervals. Both measures are deseasonalized by their respective time-of-day. The time period is December 2, 2002 to April 30, 2003.

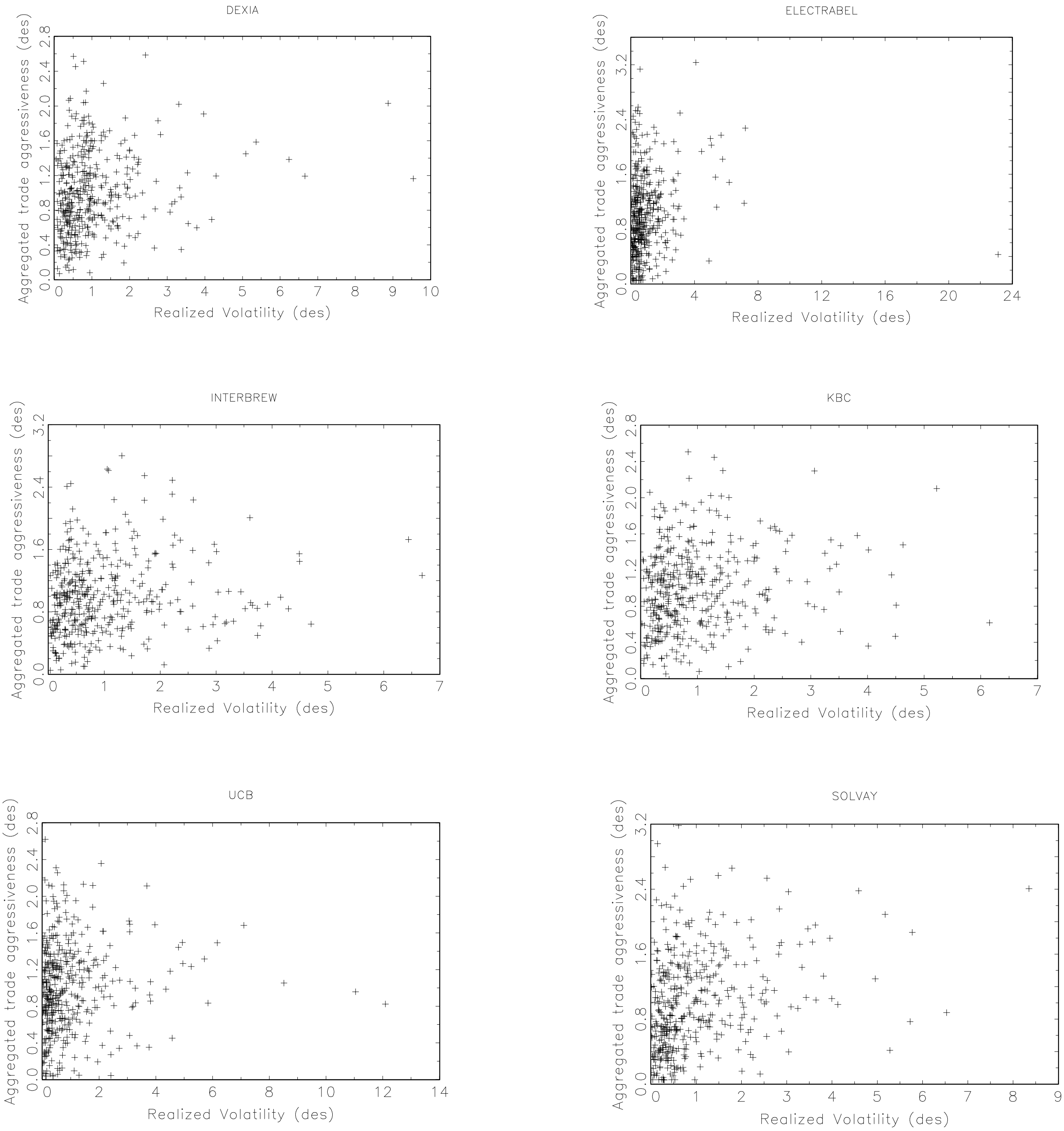

Figure 11. Aggregated trade aggressiveness vs realized volatility. Relationship between the aggregated trade aggressiveness and the realized volatility. The aggregated trade aggressiveness is the average trade aggressiveness over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals; the realized volatility is defined over the same intervals. Both measures are deseasonalized by their respective time-of-day. The time period is December 2, 2002 to April 30, 2003.

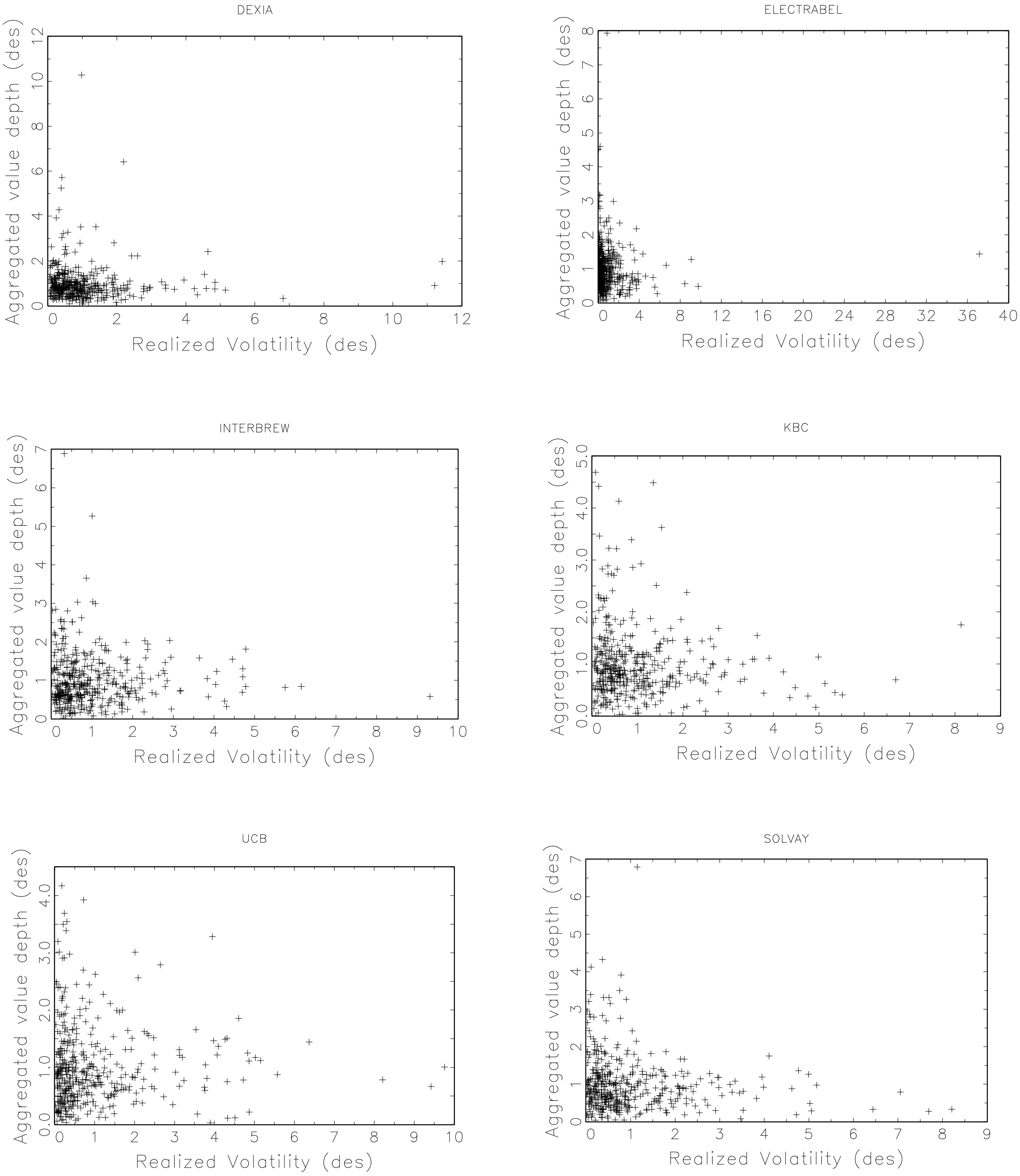

Figure 12. Aggregated bid inside depth (in euros) vs realized volatility. Relationship between the aggregated bid inside depth (in euros) and the realized volatility. The aggregated bid inside depth (in euros) is the average bid inside depth (in euros) over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals; the realized volatility is defined over the same intervals. Both measures are deseasonalized by their respective time-of-day. The time period is December 2, 2002 to April 30, 2003.

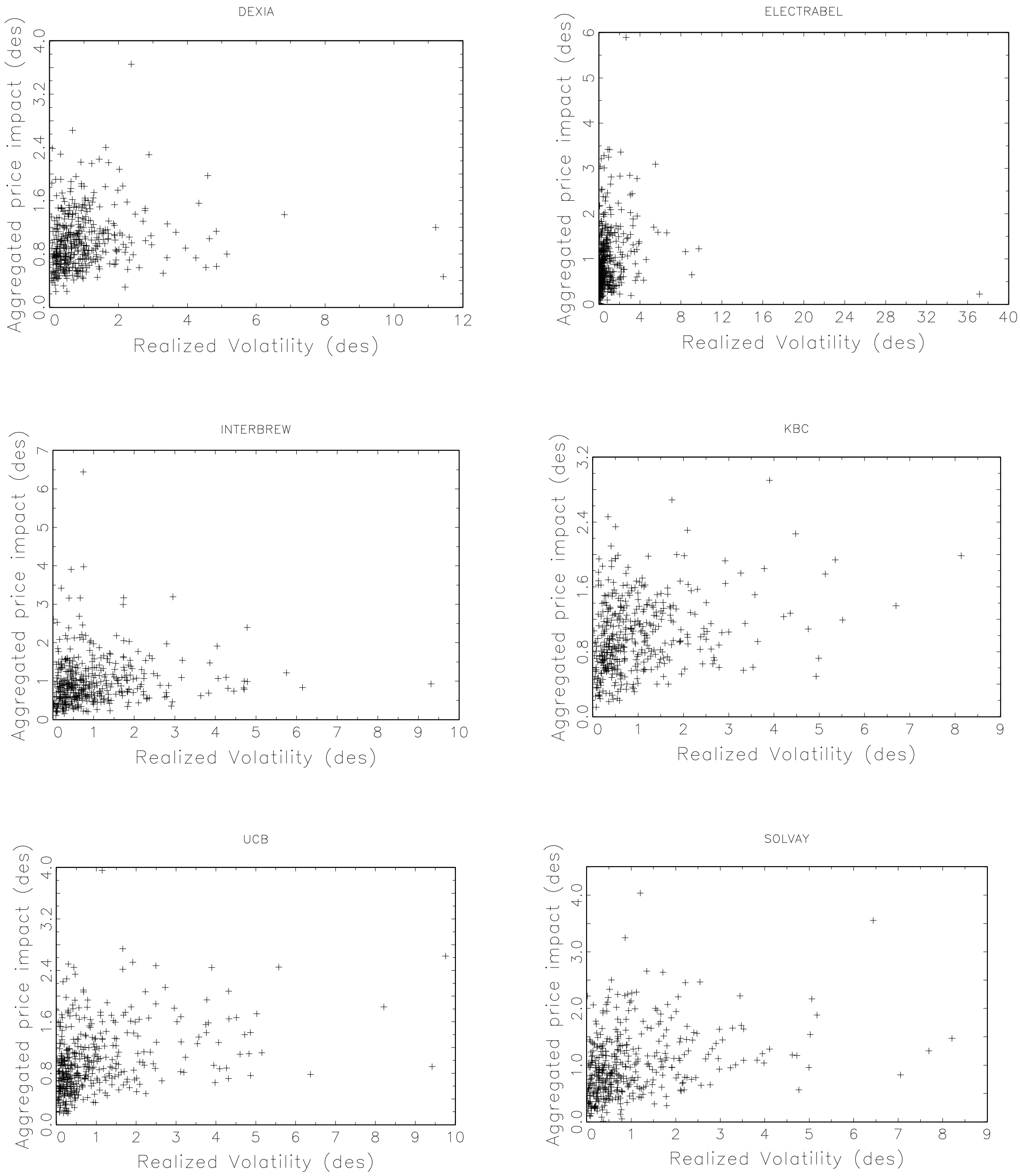

Figure 13. Aggregated bid price impact (level 3) vs realized volatility. Relationship between the aggregated bid price impact (level 3) and the realized volatility. The aggregated bid price impact (level 3) is the average bid price impact (level 3) over the [9h:11h], [11h:13h], [13h:15h] and [15h:17h30] intervals; the realized volatility is defined over the same intervals. Both measures are deseasonalized by their respective time-of-day. The time period is December 2, 2002 to April 30, 2003.

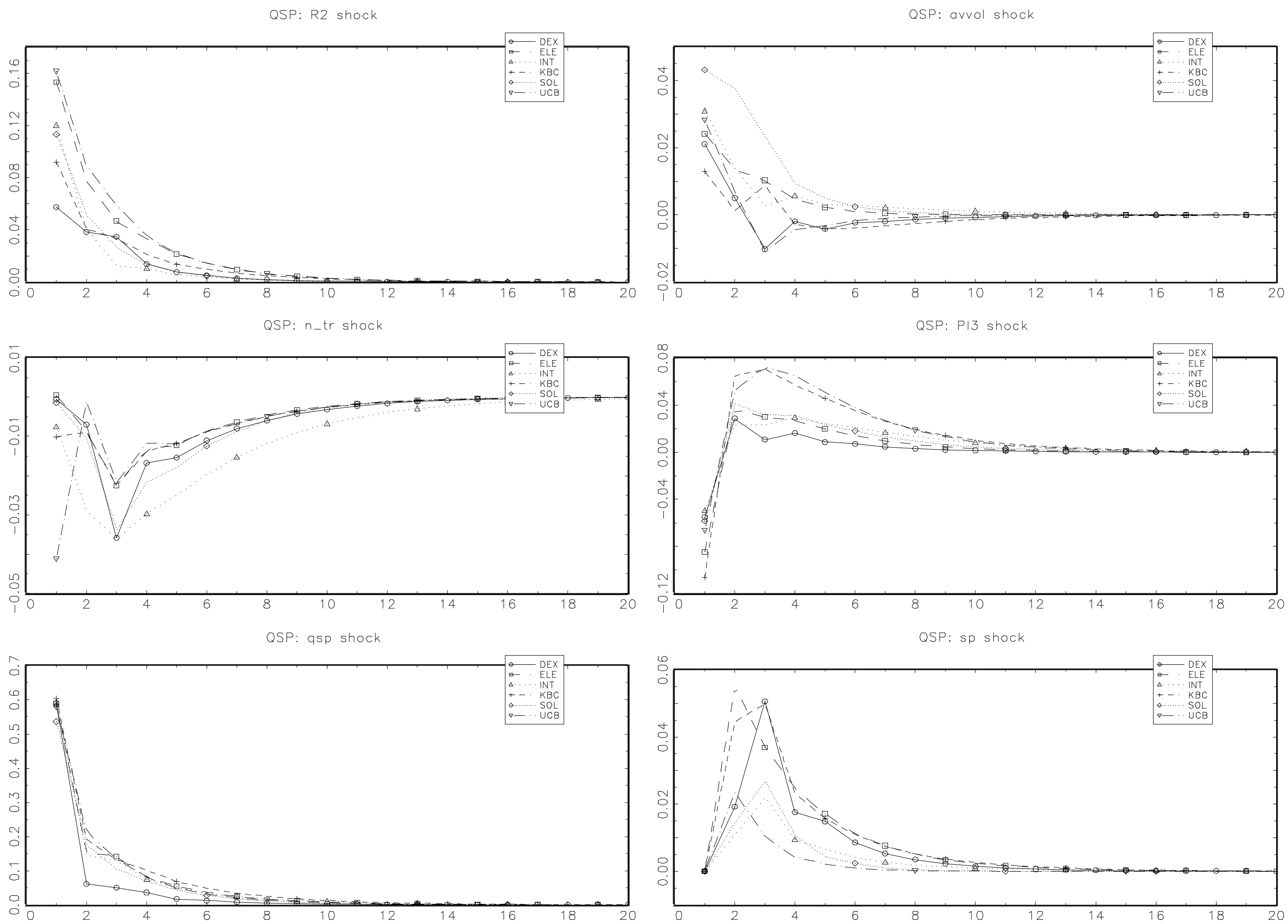

Figure 14. Impulse response functions of the inside spread, low-volatility regime. The figures report the impulse response functions of the inside spread (QSP) to a one-unit shock to the other 6 variables: volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

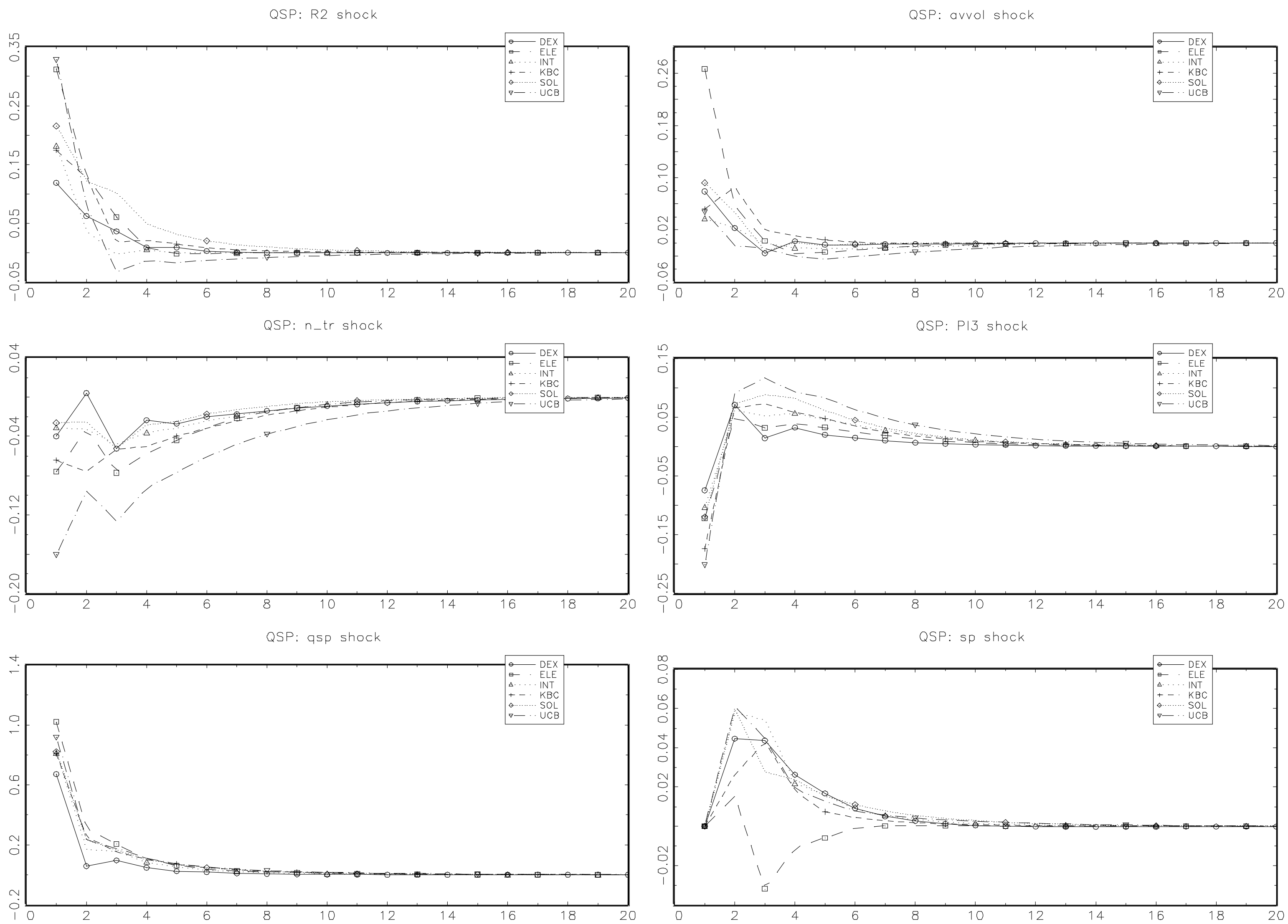

Figure 15. Impulse response functions of the inside spread, high-volatility regime. The figures report the impulse response functions of the inside spread (QSP) to a one-unit shock to the other 6 variables: volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

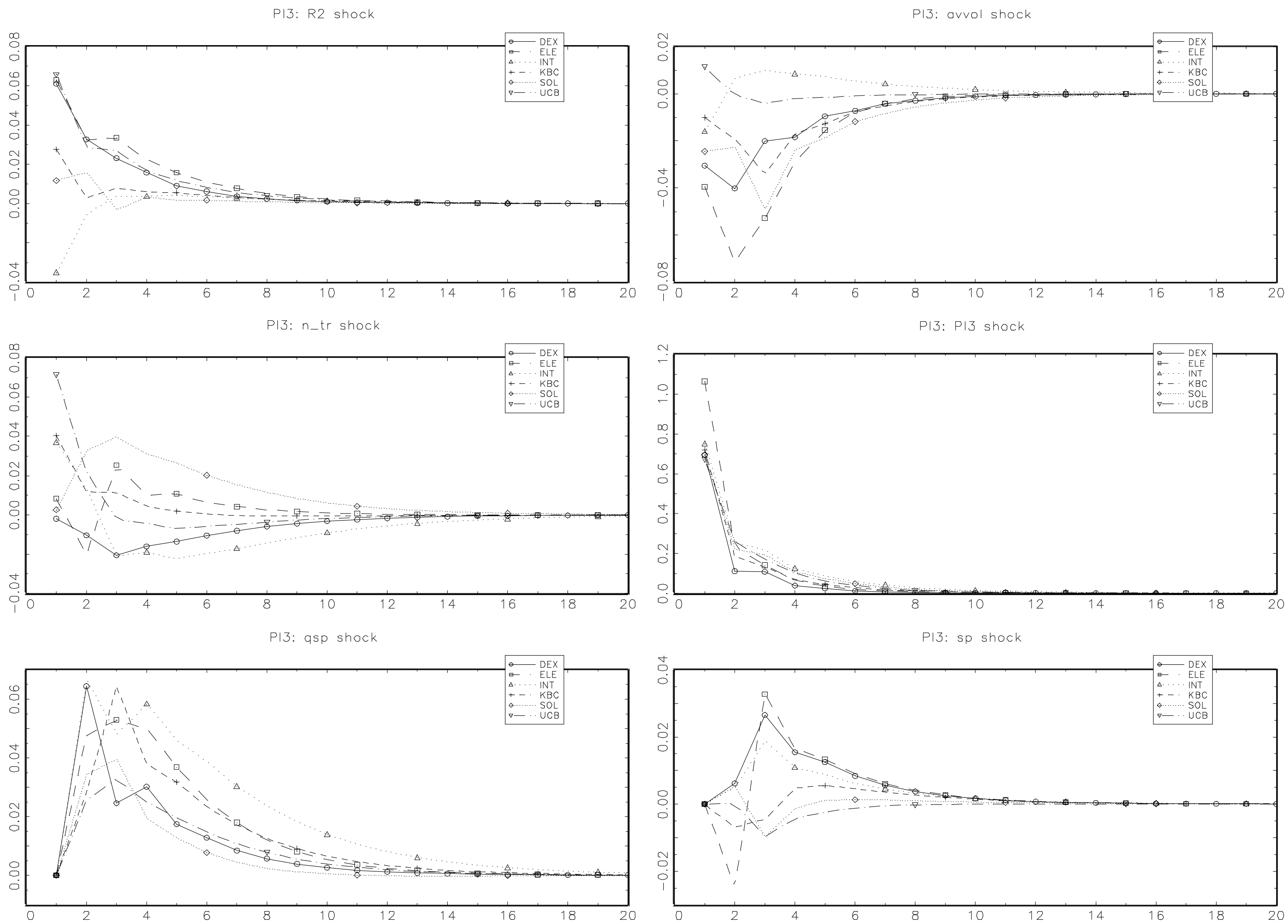

Figure 16. Impulse response functions of the price impact, level 3, low-volatility regime. The figures report the impulse response functions of the price impact for a trade of 45,000 euros (PI3) to a one-unit shock to the other 6 variables: volatility (R2), inside spread (QSP), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

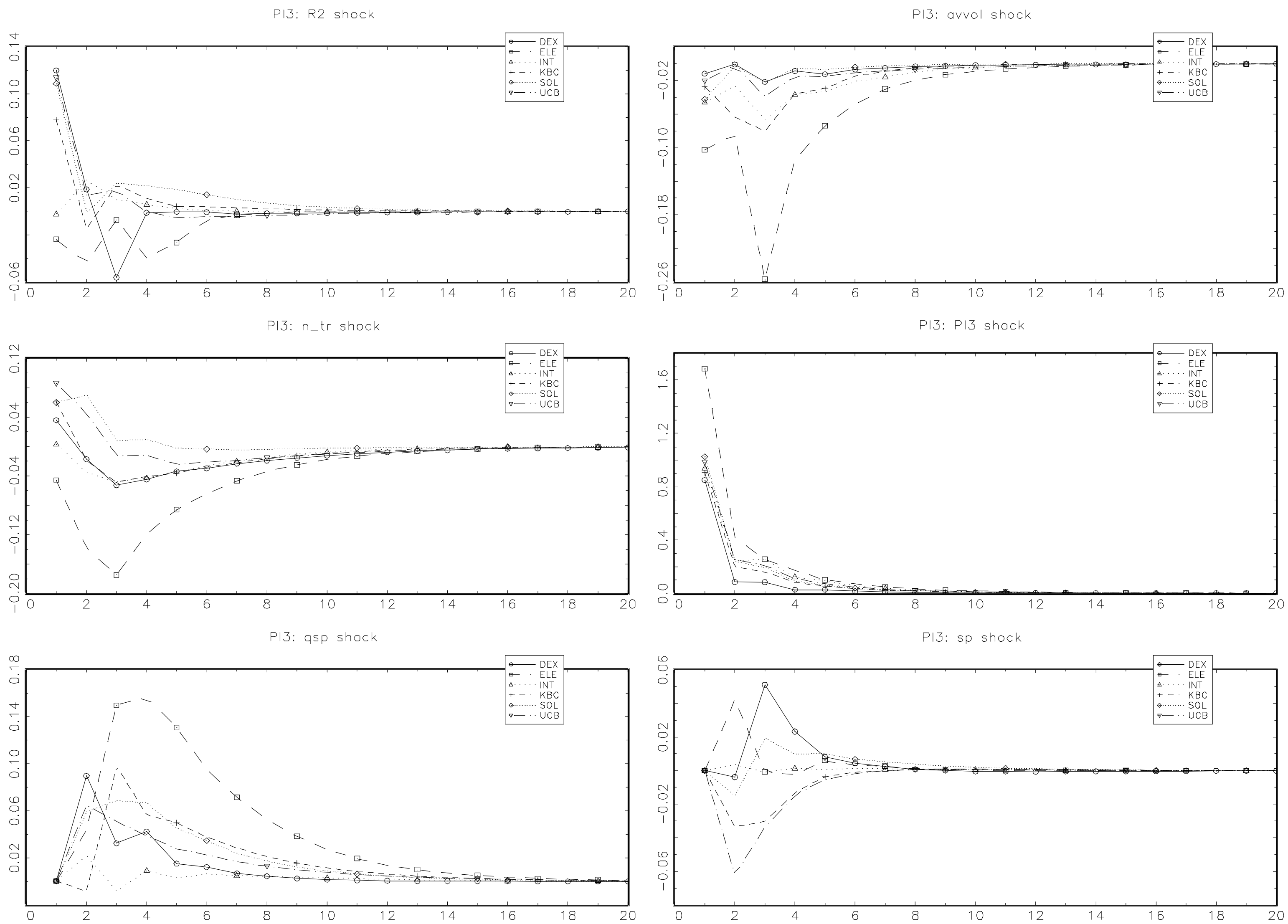

Figure 17. Impulse response functions of the price impact, level 3, high-volatility regime. The figures report the impulse response functions of the price impact for a trade of 45,000 euros (PI3) to a one-unit shock to the other 6 variables: volatility (R2), inside spread (QSP), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

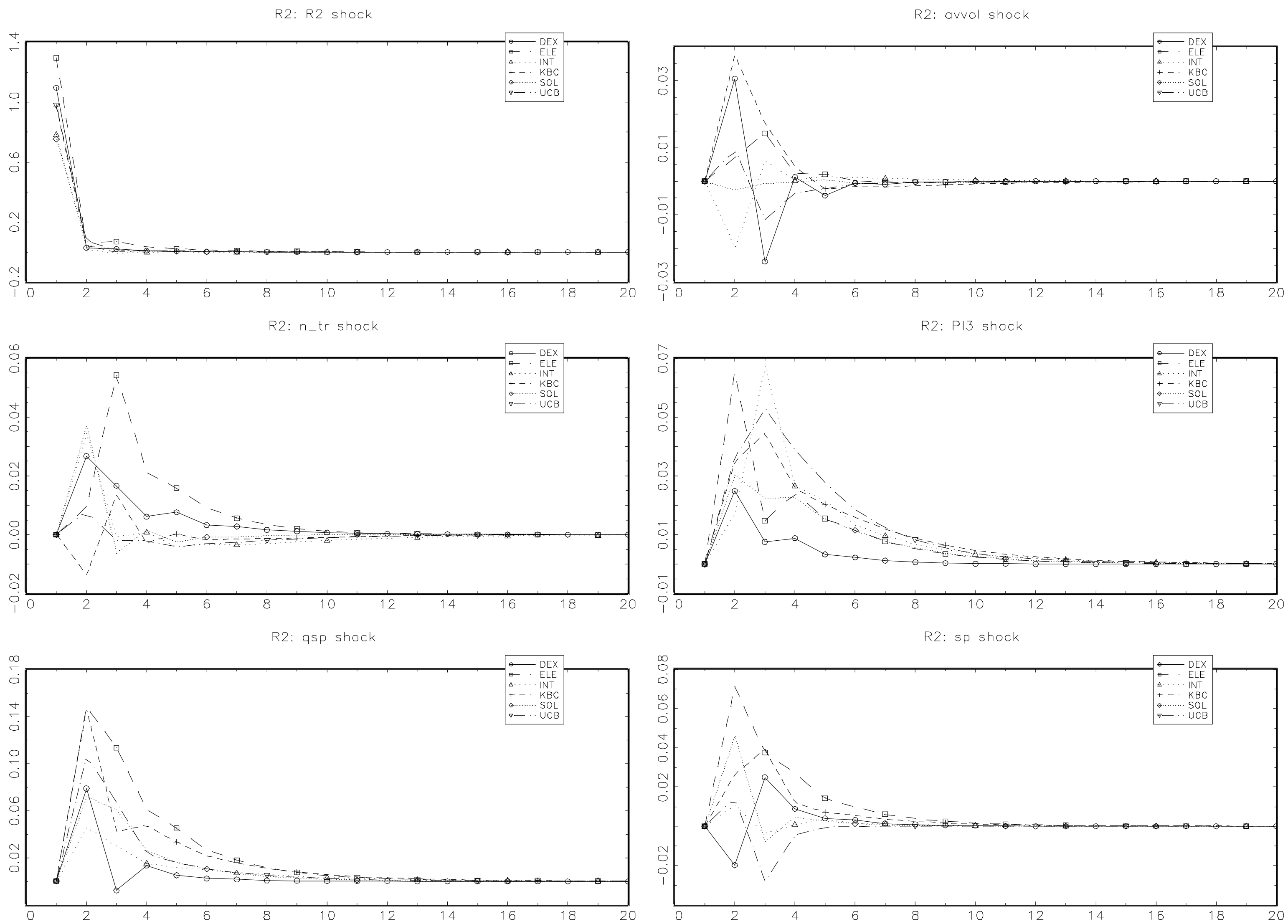

Figure 18. Impulse response functions of the volatility, low-volatility regime. The figures report the impulse response functions of the volatility (R2) to a one-unit shock to the other 6 variables: inside spread (QSP), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

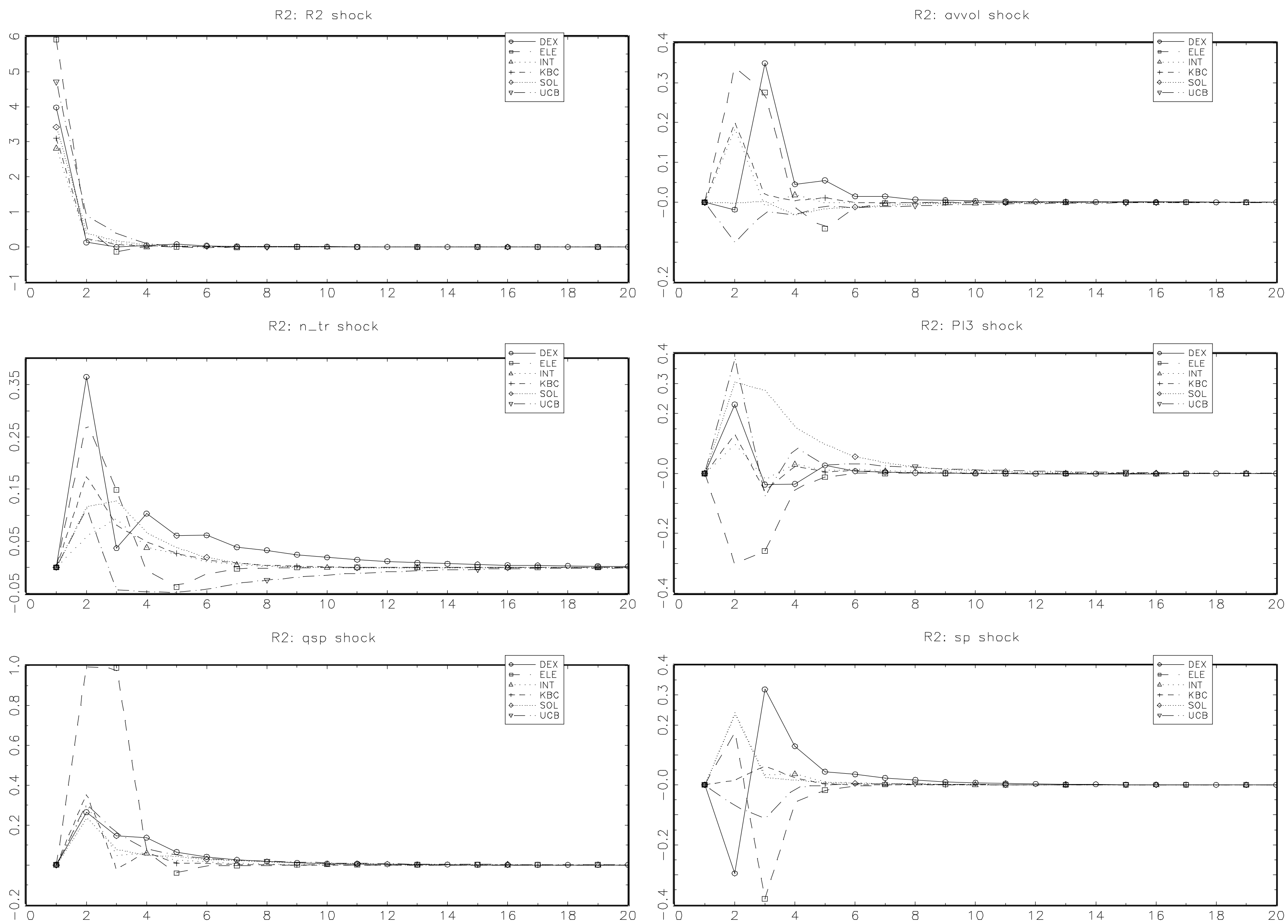

Figure 19. Impulse response functions of the volatility, high-volatility regime. The figures report the impulse response functions of the volatility (R2) to a one-unit shock to the other 6 variables: inside spread (QSP), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

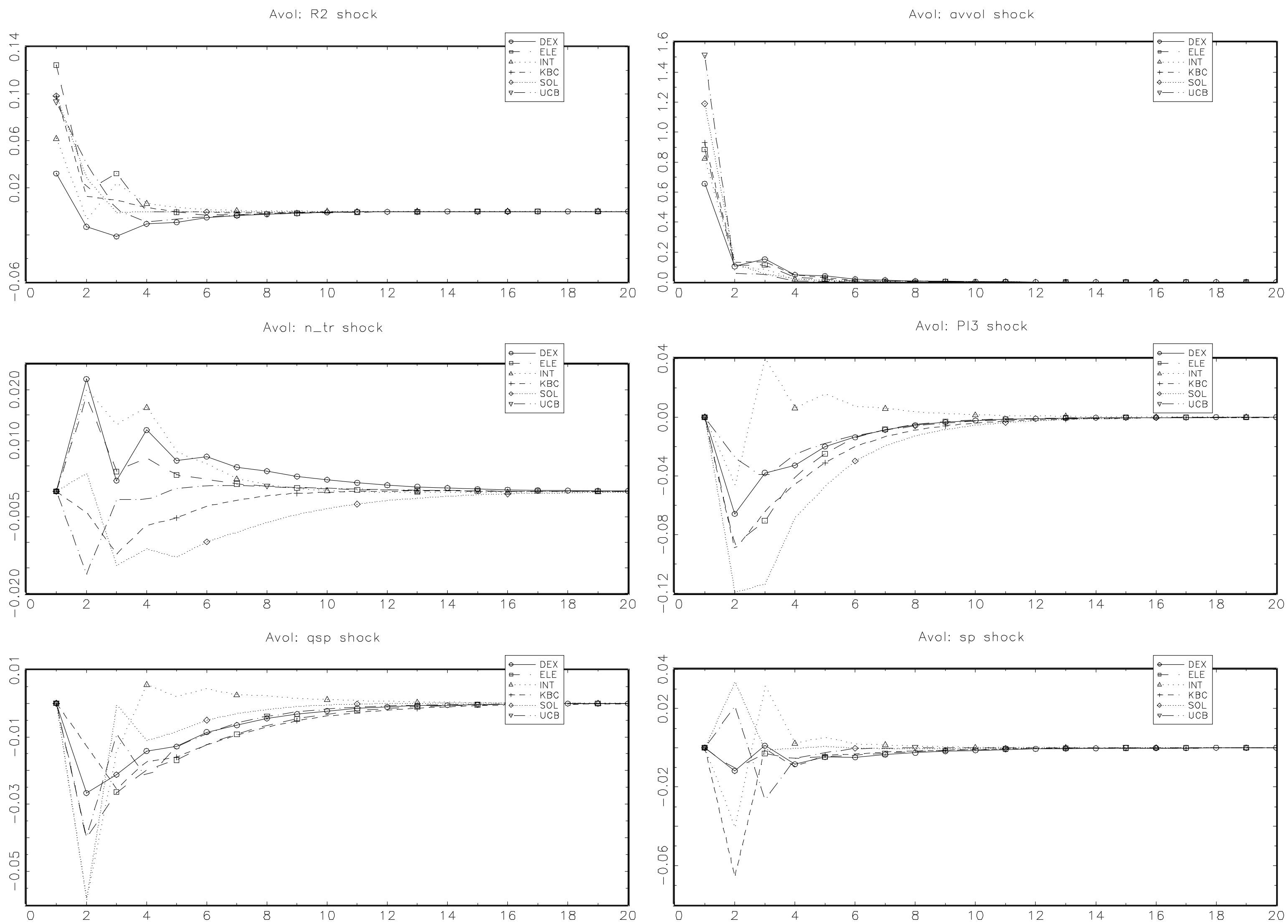

Figure 20. Impulse response functions of the average volume per trade, low-volatility regime. The figures report the impulse response functions of the average volume per trade (AVVOL) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

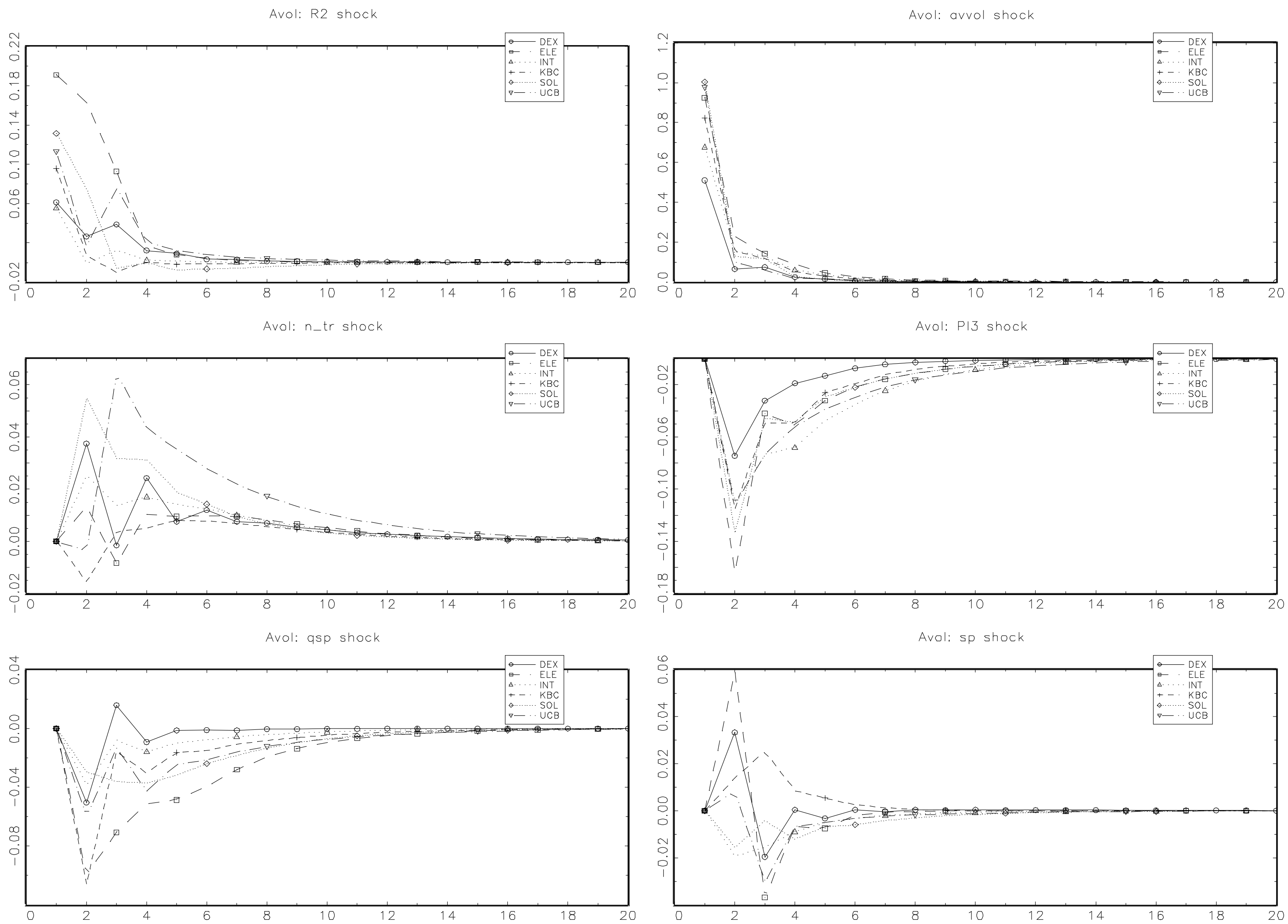

Figure 21. Impulse response functions of the average volume per trade, high-volatility regime. The figures report the impulse response functions of the average volume per trade (AVVOL) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

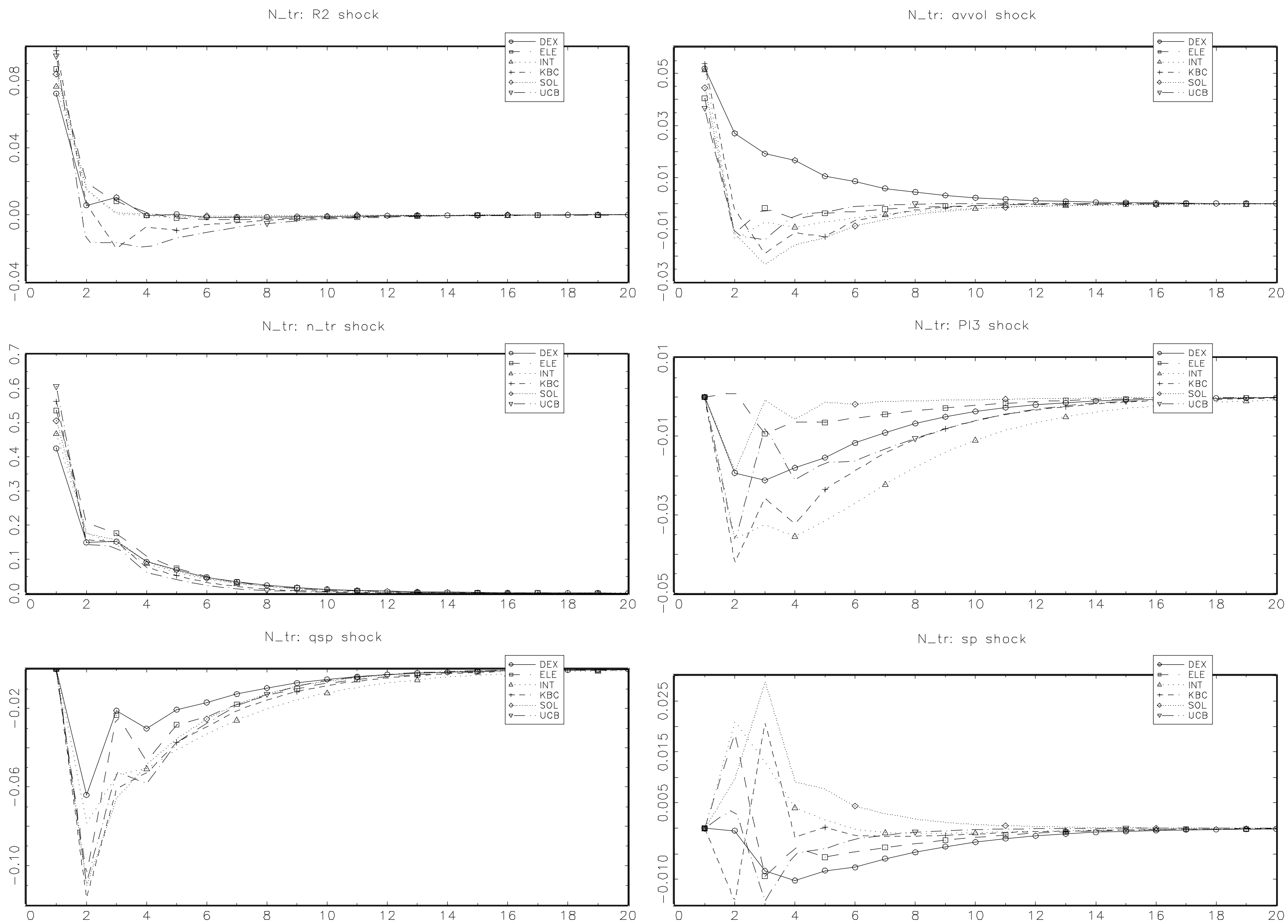

Figure 22. Impulse response functions of the number of trades, low-volatility regime. The figures report the impulse response functions of the number of trades (N_TR) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

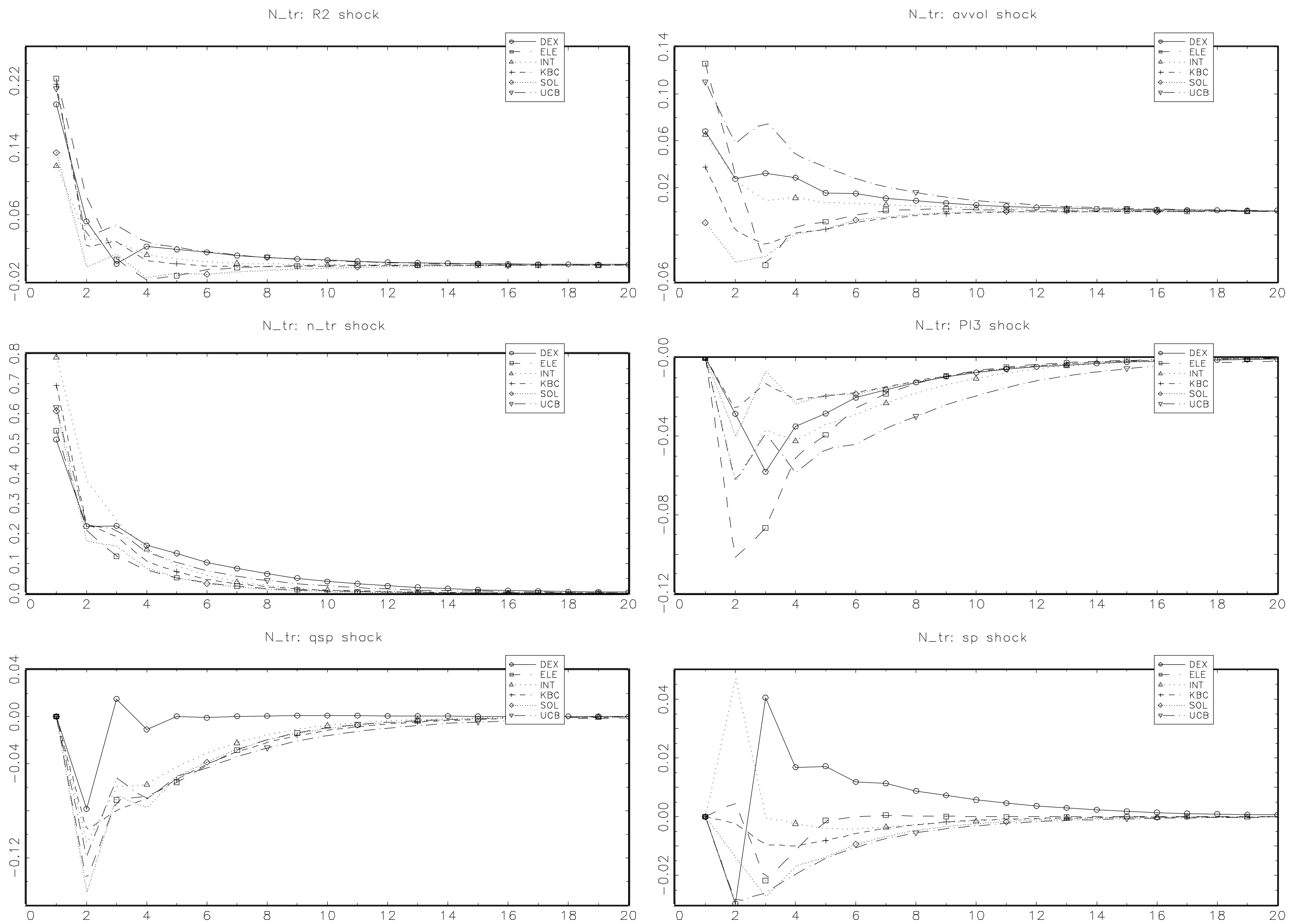

Figure 23. Impulse response functions of the number of trades, high-volatility regime. The figures report the impulse response functions of the number of trades (N_TR) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

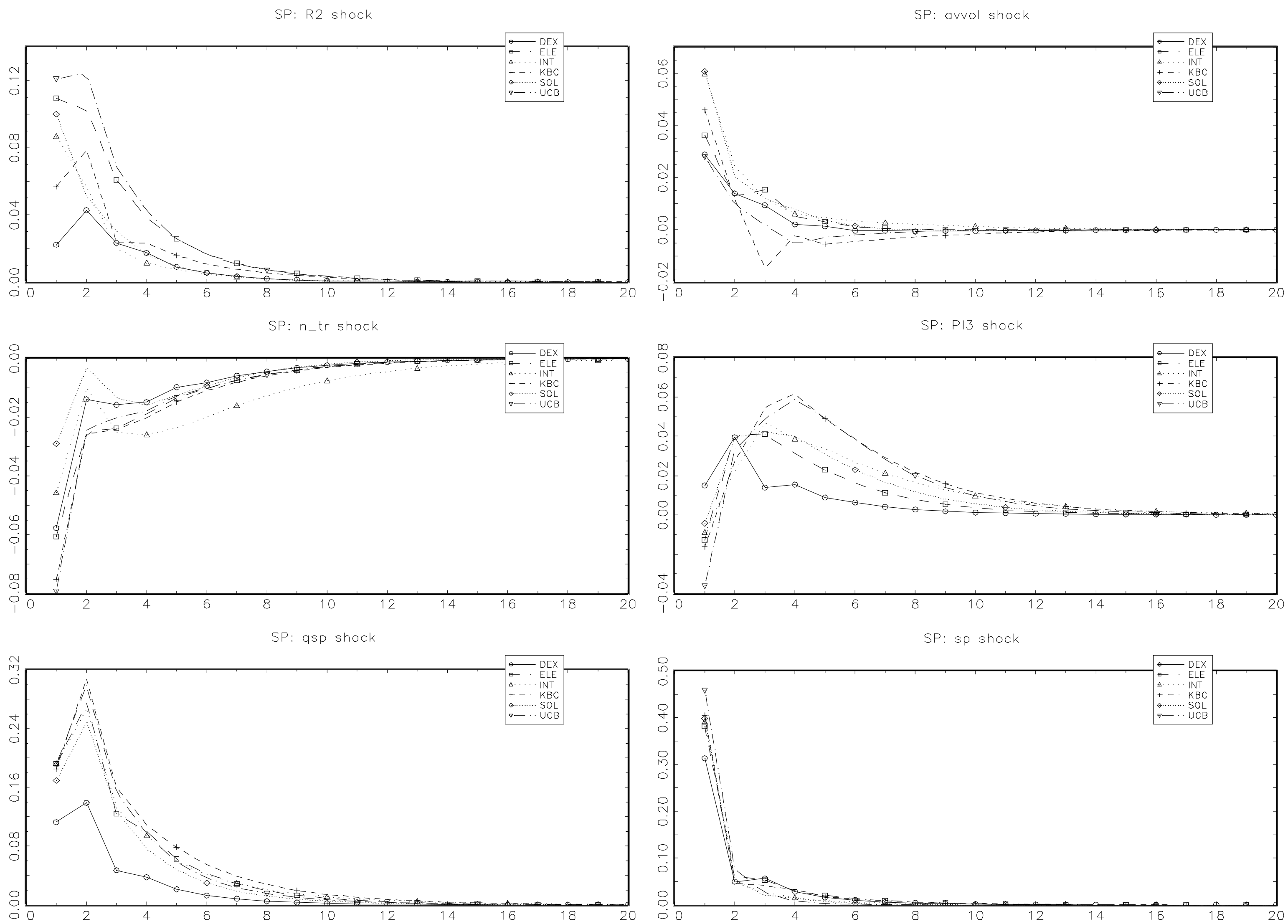

Figure 24. Impulse response functions of the effective spread, low-volatility regime. The figures report the impulse response functions of the effective spread (SP) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the low-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

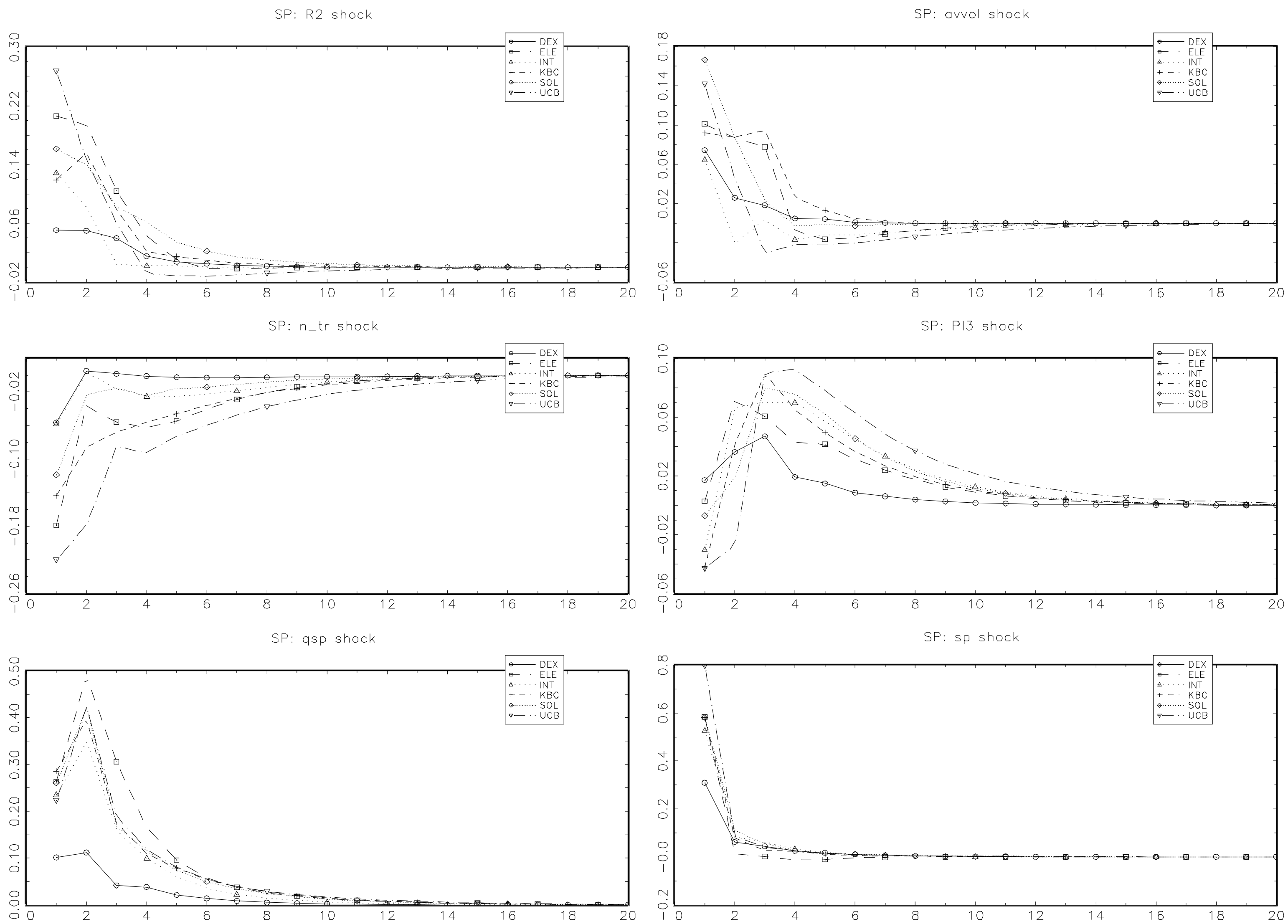

Figure 25. Impulse response functions of the effective spread, high-volatility regime. The figures report the impulse response functions of the effective spread (SP) to a one-unit shock to the other 6 variables: inside spread (QSP), volatility (R2), price impact for a transaction of 45,000 euros (PI3), number of trades (N_TR), average volume per trade (AVVOL), effective spread (SP), and itself. The impulse responses are reconstructed by means of a Cholesky decomposition from a VAR(2) model estimated with the high-volatility regime observations only. The 6 stocks are DEXIA (DEX), ELECTRABEL (ELE), INTERBREW (INT), KBC (KBC), SOLVAY (SOL), and UCB (UCB).

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