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# WORKING PAPER

# Bid-Ask Spread Components on the Foreign Exchange Market: Quantifying the Risk Component

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# Bid-Ask Spread Components on the Foreign Exchange Market: Quantifying the Risk Component*

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## Abstract

We study the tightness of the complete electronic interbank foreign exchange market for the HUF/ EUR over a two year period. First, we review the cost components that a liquidity provider on this type of market faces, and integrate them in an empirical spread decomposition model. Second, we estimate the bid-ask spread components on an intraday basis, and find that order processing costs account for 47.09% of the spread and that, the combined inventory holding and adverse selection risk component accounts for 52.52% of the spread. In addition, we provide evidence for an endogenous tick size that accounts for one third of the order processing costs and we also estimate the number of liquidity providers based on the risk component. Third, we apply the model to some interesting spread patterns. Using our model we investigate the stylized difference in spreads between peak-times and non-peak times. We find that the combined compensation for inventory holding and adverse selection risk increases during non-peak times, particularly because the risk that a liquidity provider will have to carry an inventory overnight rises. Furthermore, we apply the model to the interesting spread pattern around a speculative attack. Here, credibility of the exchange rate band, competition amongst liquidity providers and increased volatility are key in understanding what happens during this episode of extreme turmoil.

JEL: F31, G15

Keywords: microstructure, foreign exchange, spread, Hungary, inventory, adverse selection, liquidity

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# Bid-Ask Spread Components on the Foreign Exchange Market: Quantifying the Risk Component

## 1. Introduction

Liquidity captures how easy it is to convert an asset into cash, and is a key-variable of interest when investigating financial markets. Moreover, liquidity also determines the speed at which information about an asset can be processed and it as well affects the asset's expected return. From a society point of view, liquidity is important for the stability of the global financial system. In the literature, many different indicators are used to characterize the liquidity of a market. In fact, liquidity can be seen as a multi-dimensional variable: one can distinguish volume (how much trade there is on a market), depth (the quantity available on the market over different prices), immediacy (the speed at which an order can be executed), resiliency (the speed at which new orders enter the market if the quantity available on the market gets depleted) and tightness (the difference between what you pay when you buy an asset and what you get when you sell an asset).[1] In this work we focus on this last dimension – the tightness/ bid-ask spread – on a specific foreign exchange market. It is this bid-ask spread that is the cause of a difference between the price at which transactions take place and the theoretical mid-quote observed on the market. These costs are important for market participants and influence the price discovery process.[2] We aim to contribute to the understanding of this liquidity dimension by investigating the link with the different types of costs that liquidity providers face.

From the first paper that introduced an early concept of market microstructure onwards (Garman (1976 )), bid-ask spreads received a considerable amount of attention in what later became a distinct field of finance research.[3] The price difference between bid and ask prices is in general treated as a compensation for the costs liquidity providers incur on the market. Their costs can be divided in three categories: order processing costs, inventory holding costs and adverse selection costs (Tinic (1972 )). There exists a vast amount of work that tries to

[1] Concerning the definition of tightness, every transaction of course involves a buyer and a seller. To be more specific, the bid-ask spread is the difference between the price an active buyer pays and the revenue an active seller receives.
[2] For the HUF/ EUR market, which represented in 2004 only 0.22% of the global turnover on the FOREX market, this cost sums up to 59.99 Million EUR in 2003 and 61.85 Million EUR in 2004.
[3] In this early model, the spread emerged as a result of dealers who set optimal bid and ask quotes assuming that market activity follows a Poisson-process.

seize the importance of each of these components. Early structural models include (Ho and Stoll (1981); Huang and Stoll (1997); Stoll (1978 )). Empirical models follow a somewhat different approach and do not impose a complete structural model that describes the trading process. They do not impose strong assumptions on the behaviour of traders and the way how they interact, but model each component separately and explicitly (the most notable example – that inspired us and to which we will refer a lot – being developed by Bollen, Smith and Whaley (2004)).

In this paper, we will apply an empirical spread decomposition model to a very extensive dataset on Hungarian forint/ Euro interbank trading for 2003 and 2004. The Hungarian forint was traded exclusively vis-à-vis the Euro during this sample period (trades from other currencies took place by using the Euro as vehicle currency). The HUF/ EUR is a minor market, which accounted for 0.22% of the global turnover in 2004 (BIS (2004 )), and according to the latest record accounts for 0.4% of the global turnover (BIS (2010 )). An interesting characteristic of the HUF/ EUR market is that there was a strong liquidity increase/ transaction cost decrease over the sample period. This strong liquidity variation over a relatively short amount of time is the result of an integration process, and distinguishes this foreign exchange market from others.

A typical feature of the interbank foreign exchange market that we study, is that it has no designated market makers. Still, attracted by potential profits, some participants can play the role of liquidity provider. This leads to the emergence of what has been labelled endogenous liquidity provision in theoretical, experimental and empirical work (Anand and Venkataraman (2013); Bloomfield, O'Hara and Saar (2005 )). For the same HUF/ EUR market, and using the same data, it was argued that endogenous liquidity providers were active around jumps (Frömmel, Han and Van Gysegem (2013 )).

The contribution of this paper is at least threefold. First, we provide results of an empirical spread decomposition model for the foreign exchange market. Although the literature refers often to insights from the empirical spread decomposition model, results for this type of model are relatively scarce. Full results are currently only available for Nasdaq stocks. Our work allows to review the impact on the results of the very different microstructure of this type of market (e.g. specialists vs. endogenous liquidity providers). Second, we apply the model on an intraday, hourly basis. This frequency is more in line with the frequency at which liquidity provision takes place. An additional advantage is that the intraday pattern is not averaged out. Furthermore, we take the partly fixed and partly variable nature of order processing costs into account. Third, we provide some interesting applications of this type of models: we look to the stylized intraday spread pattern from a cost component perspective and we apply the model to a period of major turmoil on the market (i.e. a speculative attack against the Hungarian forint).

## 2. The foreign exchange market: characteristics and advantages

The foreign exchange market is the largest financial market in the world: the daily turnover of the global foreign exchange spot market was for 2010 estimated at $ 1.5 trillion (BIS (2010 )), which is approximately 15 times the global GDP that is generated on a daily basis.[4] In addition to its overwhelming size, the foreign exchange market has some other distinctive features. First of all, the market has a two-tier structure. One tier consists of trade between customers and banks. The customers are then the actual end-users of the currencies and can be further split up in non-dealer financial institutions on the one hand (such as hedge funds) and corporations and governments on the other hand (such as importing and exporting firms). However, also retail investors and algorithmic traders represent an increasing amount of the trading activity (King, Osler and Rime (2011 )).[5] A second tier consists of interbank trading. It is in this second tier that the price formation takes place and where the spot exchange rates are set. These spot exchange rates are the reference prices for all other foreign exchange deals (e.g. on the dealer-customer market). A second distinctive feature of the foreign exchange market is that it is a decentralized market (without designated market makers). It is an electronic, order-driven market where participants can trade by posting a market order or a limit order. A market order is immediately matched with the best available outstanding order at the opposite side of the book. Limit orders stay in the book until they are matched with an incoming market order or until they are cancelled by the participant who placed the order. A third distinctive feature is that there are no official opening and closing times (in principle, there are trades 24h a day except for the weekends).

The foreign exchange market has advantages over other markets for microstructure researchers. First of all, trading is really continuous as it is not interrupted by specific opening/ closing procedures and/ or batch auctions that lead to breaks in the timeseries. Secondly, many participants have access to this market, and they can all observe all outstanding buy and sell orders in the marketplace (there is no hidden liquidity, like iceberg

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[4] Assuming on average 20 working days per month. The Worldbank estimates the global GDP for 2010 at $ 63 trillion.

[5] Their share in trading on the overall foreign exchange market has risen from 20% in 1998 to more than 50% in 2010.

orders etc.). It is therefore often argued that the foreign exchange market is the real-world market that resembles perfect competition most closely. This is in line with the assumptions behind most models in microstructure research, and makes the interpretation of our results less ambiguous. The specific dataset we are working with offers additional advantages: it is a very complete dataset (we cover all electronic trading of this currency pair), and it has an unusually long time span of two years. These characteristics ensure the representativeness and robustness of the results we obtain, and allow us to investigate the variation over time.

## 3. Cost components of the bid-ask spread

The bid-ask spread is the source of revenues for liquidity providers. However, providing liquidity also comes with a cost. The first to categorize these costs was Tinic (1972). He identified three broad cost components, and his categorization was the starting point for an extensive literature that deals with the theoretical modelling of these costs and testing their empirical relevance.

*Order processing costs (OPC)*

The first category concerns the general costs of providing market making services. These costs are partly fixed (e.g. wages of traders, floor space rent, subscriptions to trading platforms and information providers,…). These fixed costs have to be covered while providing liquidity, and can be spread over all transactions of the liquidity providers. Another part of the order processing costs is variable and thus incurred each time there is a trade (e.g. exchange, clearing and settlement fees, attention by traders,… ). The fact that part of the order processing costs is variable has implications for the spread and price dynamics.[6]

*Inventory holding costs (IHC)*

Secondly, providing liquidity implies that you take positions and hold an inventory. This inventory is unwanted in the sense that a liquidity provider does not want to be exposed to price movements. Theoretical models predict that this results in a process in which liquidity providers adapt their spread based on their inventory of risky assets. They change their quotes in order to induce inventory equilibrating trades (Amihud and Mendelson (1980); Ho and Stoll (1981 )). In addition to the risk of an adverse price movement, holding an inventory also

[6] For variable order processing costs and an interesting model dealing with the implications for price dynamics, see p.101-106 of Foucault, Thierry, Marco Pagano, and Ailsa Röell, 2013, Market liquidity: Theory, evidence and policy, (Oxford University Press, USA).

comes with an opportunity cost for the funds invested in the inventory, as this inventory needs to be financed on a continuous basis (Demsetz (1968 )).

*Adverse selection costs (ASC)*

Thirdly, there is also a cost associated with engaging in a transaction with a market participant who has superior information. The first to analyse the asymmetric information problem for a dealer when she has to decide on the bid and ask quotes was (Bagehot (1971 )). A formal treatment of this problem involves splitting up the market participants looking for execution into two categories, based on their motivation: informed traders, who have private information on the real value of the underlying quote, and uninformed traders (Glosten and Milgrom (1985 )). This last category was initially considered to trade for liquidity reasons or to hedge themselves. Later, another type of traders was added: traders who think they have private information without actually having it. This subcategory can then be labelled as noise traders.[7] Both informed and uninformed traders pay the spread in order to get executed. The informed traders know, however, that when selling (buying), the bid (ask) quote they get (pay) is too high (low), and does not correspond to the true, underlying value. Liquidity providers only know that this type of traders exists, but cannot know in advance whether a specific trade is liquidity or information motivated. This leads to a problem of adverse selection, and liquidity providers will ask a compensation for the associated risk. While Glosten and Milgrom (1985) treat this problem in a quote driven framework where traders arrive sequentially, Kyle (1985) models this problem in an order driven framework, similar to a batch auction. This last setting is more similar to the foreign exchange market.

As a clarification, adverse selection costs are not linked to the presence of information per se in the market. When the information is symmetric, there will be no adverse selection cost for the liquidity provider. The risk of new, symmetrically spread, information disclosed after the transaction and leading to price movements is fully contained in the inventory holding costs.

## 4. Model

Above we outlined the theoretical foundations for the main cost categories that liquidity suppliers face when they want to add liquidity to the book. In this chapter we will follow the literature in assuming that the spread is a function of these three cost components:

[7] For an extensive discussion that clarifies the difference between these different types of traders (which are used in many cases interchangeably), see Bloomfield, O'hara and Saar (2009).

$$SPRD_i = f(OPC_i, IHC_i, ASC_i) \quad \text{(Eq. 1)}$$

We now develop an empirical spread decomposition model and focus on how to model each cost component.

*Order processing component*

Because of their partly fixed nature, order processing costs are expected to be negatively related to the volume traded. Empirical work found evidence for this negative relation between some measure of volume traded and the spread (Bollen, Smith and Whaley (2004); Branch and Freed (1977); Harris (1994); Stoll (1978); Tinic (1972); Tinic and West (1972); Tinic and West (1974 )). However, volume traded also carries information. When splitting up the volume traded in an expected and an unexpected component, one could argue that unexpected deviations from normal intraday trading volume point at private information, and consequently push the exchange rate up or down. This was confirmed in various empirical studies (Danielsson and Payne (2011); Easley and O'Hara (1992 )). This substantial part of the volume traded will by consequence rather be related to private information, and not to order processing costs. Additionally, it has been noted that the relation between volume traded and spread could be obfuscated by the fact that participants are active on multiple markets over which they can distribute their fixed costs. Moreover, above we referred to the notion that not all costs of order processing are fixed: some of them are incurred each time there is a trade. We include this in our model as a constant that is not depending on the volume traded.

Following the insights on the nature of order processing costs (partly variable, partly fixed) and the nature of volume traded (partly expected, partly unexpected) we model the OPC as partly fixed and partly depending on the expected volume traded. Here we differ from Bollen, Smith and Whaley (2004). This specification is consistent with a broad definition of order processing costs, which includes clearing and settlement fees, tick-size and non-competitive rents.[8] All these costs have in common that they are covered by revenues under the form of a mark-up (partly a mark-up per trade, and partly a mark-up over all expected trades per interval) on top of the risk components. The resulting order processing costs per time-interval are consequently modelled as:

[8] A separate variable indicating the level of competition, such as the modified Herfindahl index, would make it possible to split this component further up. This data is, however, not available. For an extensive analysis of the link between competition and bid-ask spreads on this type of markets, see Huang and Masulis (1999).

$$OPC = \alpha_0 + \alpha_1 Exp\, TV_i \qquad \text{(Eq. 2)}$$

With OPC being equal to the order processing cost and EXP TV being equal to the expected volume traded.

*Risk component*

The notion that liquidity providers are aware of the risk of adverse changes in the price of assets in their inventory (inventory holding costs) was tested empirically in the literature using various proxies for these price changes. A logical class of proxies for price movements that can be easily transferred to the foreign exchange market are volatility-related proxies. For different markets, a positive relation between volatility and bid-ask spreads was reported (Bollerslev and Melvin (1994); Branch and Freed (1977); Harris (1994); Stoll (1978); Tinic (1972 )).

The presence of asymmetric information (adverse selection costs) in a market is, because of its very nature, difficult to detect for market participants and researchers. Early ex post proxies on equity markets included inter alia the number of specialist stocks in which a certain market maker was active (Tinic and West (1972 )) and trading volume over market capitalization (Stoll (1978 )). On the foreign exchange market different adverse selection proxies were used. Some authors used quoting frequency on the Reuters EFX system (Phylaktis and Chen (2010 )). The more active in quoting on Reuters, the more informed a bank seems to be. Related to this, the size of the counterparty (Bjønnes, Osler and Rime (2008 )) was also shown to be related to private information. These authors find that large traders are the most informed (and connect in that way with what Stoll (1978) found for the equity market). Another, interesting approach consists of looking to the price impact (Menkhoff and Schmeling (2010 )). Using an extensive inter-dealer FX trading dataset with counter-party identities, it has been shown that orders by counterparties who have superior information have a greater price impact (Moore and Payne (2011 )). Finally, asymmetric information was also found to be related to order flow characteristics. Theoretical models have shown that information enters the market when informed participants take liquidity, rather than when participants add liquidity (Evans and Lyons (2006); King, Sarno and Sojli (2010 )). Additionally, when dealers think they have information (e.g. after accepting a large order from a financial institution on the customer-side) they are found to take liquidity in the direction of the information (Bjønnes, Osler and Rime (2008); Osler, Mende and Menkhoff

(2011 )). In a next stage, it is widely documented that, because of their (private) information content, order flow drives the price in the spot FX market (Evans and Lyons (2002 )).

In general terms, one can treat this two risk components in one common framework. The compensation required by the liquidity provider for taking the inventory holding and the adverse selection risk after accommodating, for example, a sell order will be equal to the expected loss when the quote moves adversely times the probability of an adverse quote movement:

$$RISK = -E(\Delta S \mid \Delta S < 0) \cdot \Pr(\Delta S < 0) \qquad \text{(Eq. 2)}$$

Bollen, Smith and Whaley (2004) show that the expected cost of accommodating an order can be quantified as the price of an at-the-money option with the time that the stock is held in inventory as expiration. This finding is very intuitive: such an option would yield a pay-off structure that is compensating the loss when the price of the asset in inventory changes adversely. For example, if a liquidity provider has no inventory and is accommodating an active buy (sell) order, she will be short (long) the asset. A call-option (put-option) will hedge her position. The midquote immediately prior to the submission of the active order will be the true price. This will also be the strike. The combined inventory holding and adverse selection costs (the risk component) will thus be equal to an at-the-money option. The value of this option is given by (Black and Scholes (1973); Merton (1973 )):

$$RISK = S[2N(0.5\sigma\sqrt{t}) - 1] \qquad \text{(Eq. 3)}$$

With S being equal to the true price, here the midquote, σ being equal to the annualized standard deviation of the return, t being equal to the time between two offsetting trades expressed in years, and N(·) is the cumulative standard normal density function. This formula is identical for valuing an at-the money call option and an at-the-money put option.

Bollen, Smith and Whaley (2004) further explore the effect of a stochastic time between offsetting trades and also the effect of taking into account that the combined, hedged position of the liquidity provider still makes it possible to profit from advantageous price changes. They conclude that under realistic parameter settings, both features only have a minor effect on the calculated risk component.

Formally, we can now combine the cost components mentioned above in a regression model:

$$SPRD_i = \alpha_0 + \alpha_1 Exp\,TV_i + \alpha_2 RISK_i + \varepsilon_i \qquad \text{(Eq. 4)}$$

With SPRD is the observed intraday spread, Exp TV is the expected volume traded and RISK is the premium for the combined inventory holding and adverse selection risk.

## 5. Empirical results

### *5.1. Data*

In this work, we use an unusually rich and complete tick-by-tick dataset for the years 2003 and 2004. Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed via the Reuters D3000 broking system. This was the only platform that offered services for this currency pair during our sample period, so we cover the complete electronic trading. We observe the price, the quantity in Euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. We use the data to reconstruct the limit order book at the intraday level. This allows us to determine the mid-quote and the quoted spread at any point in time. We aggregate the tick-by-tick data and information from the reconstructed limit order book (both at market event frequency) to twelve hourly observations per day (from 7am till 7pm). This way, we obtain 6060 hourly intervals which cover the hours with the highest market activity (See Figure 2 for the intraday distribution of ticks, which is a measure for how active traders are).

The quote and the volume traded over the two years contained in our dataset are shown in Figure 1. An important event clearly stands out: there was a speculative attack against the top of the currency band in January 2003, followed by a central bank intervention which brought the quote back to its target value. Table 1 presents some summary statistics.

### *5.2. The bid-ask spread and its determinants*

In this work we focus on the quoted spread, as this is the relevant spread for a market participant who is looking for execution.[9] Interdealer bid-ask spreads on currency markets are in general low. They range from roughly 0.5-2 basispoints on liquid markets to 40 basispoints on less liquid markets (King, Osler and Rime (2011); Osler, Mende and Menkhoff (2011 )).[10] We see that for our market the half-year average quoted spread lies between 0.25 HUF/ EUR and 0.39 HUF/ EUR. This corresponds to respectively 9.99 and 15.01 basispoints. We distinguish for each interval the time-weighted spread and the last spread observed in the book.[11]

The volume traded per hourly interval is expressed in million EUR. The minimum size of a trade is 1 million EUR, and all quantities traded are multiples of this minimum size. Most of the trades, 80.38%, that take place actually have the minimum size, 13.79% of the trades are for 2 million EUR and the remaining 5.83% are for at least 3 million EUR. The fact that trades for the minimum size dominate is consistent with a widespread use of order splitting strategies by traders (in an attempt to minimize the market impact, see also Kyle (1985)). The average expected volume traded increased each half year from 7.58 million EUR to 12.08 million EUR per hourly interval

The volatility is calculated as the annualized standard deviation over the last 30 ten minutes intervals, such that it reflects the volatility over a frequency that is relevant for liquidity suppliers. The distribution of these volatilities is right-skewed. The time between trades is expressed in minutes, assuming that the volume traded during each interval is evenly distributed during the interval. When used to calculate the option value, the time between two trades is annualized.

[9] Some works, especially dealing with stock market spreads, focus also partly (or fully) on the effective spread (being the difference between the price at which a transaction takes place and the prevailing quote from the other side of the book). These authors typically find that the effective spread is smaller than the quoted spread (i.a. Bollen, Smith and Whaley (2004)). This is possible because in some markets, participants can negotiate directly for a better quote, or because there is hidden liquidity available in the book. In our market, negotiations are not directly observed and there is no hidden liquidity. Therefore, the effective spread will be at least as high as the quoted spread (it will be higher if the order walks up the book). We focus by consequence only on the quoted spread.

[10] Although we should keep in mind that this is still very liquid compared to stock markets. The spread on Nasdaq stocks found by Bollen, Smith and Whaley (2004) corresponds to respectively 203.68, 108.67 and 61.88 basispoints for selective months.

[11] The time-weighted spread is calculated by multiplying each observed quote during an interval with the relative time it was observed.

### *5.3. Intraday patterns*

As we undertake an intraday analysis, we are automatically concerned about the intraday pattern that characterizes our variables. Therefore, we calculate for the two-year sample period the intraday pattern for the bid-ask spread and the quantity traded, which can be found respectively in Figure 3 and Figure 4.[12] The spread pattern is U-shaped. This contrasts to the W-shaped pattern found for the USD/ DEM spot market (Danielsson and Payne (2011 )), but is consistent with what other authors found for a wide array of foreign exchange markets (McGroarty, ap Gwilym and Thomas (2009 )). The intraday volume pattern is found to be M-shaped. This result is consistent with what other authors found for the foreign exchange market (Danielsson and Payne (2011); McGroarty, ap Gwilym and Thomas (2009 )), but differs from the widely documented U-shaped pattern on other financial markets. We will use the pattern of the quantity traded as proxy for the expected quantity traded, in order to determine the order processing component. To take changing expectations into account, the pattern of expected trading volume is updated every half-year.

### *5.4. Results*

*Bivariate correlations*

As a first step, we analyse the bivariate correlations between the variables we will use in the regression analysis (See Table 3). The correlations of all explanatory variables with the time-weighted quoted spread are significant at the 1% level.[13] The correlations with the non-time weighted quoted spread are consistently lower (and unexpected trading volume becomes even insignificant). The large difference in correlations underlines the importance of choosing the right spread variable. The input variables used to quantify the risk component have at the individual level a lower correlation with the spread (23% for volatility and 38% for the time between two trades) than the correlation between spread and the modelled component (which is 56%). The correlation between the spread and the expected quantity traded has the right sign.

In a similar analysis for a set of liquid currencies (the currency pairs consisting of USD, JPY, CHF and EUR (DEM)), a very low correlation between the bid-ask spread and the volatility (1%-9%) was found (McGroarty, ap Gwilym and Thomas (2009 )). The low results were, according to the authors, evidence for the hypothesis that liquidity provision on the

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[12] These patterns were obtained using the median, and not the mean, to increase robustness.

[13] We use a t-test, with $t = \frac{correlation\,\sqrt{number\ of\ observations - 2}}{\sqrt{1 - correlation^2}}$.

foreign exchange market is very different from stock and bond markets, as no inventory needs to be managed (McGroarty, ap Gwilym and Thomas (2006 )). Our results challenge this hypothesis. Possible reasons for our different results include that the results in the former work were obtained using the last quotes for each interval and not the time-weighted quotes, and that we are dealing with a less liquid currency for which the inventory risk is obviously bigger.

*Decomposition results*

In Table 4 we present the results for the intraday empirical spread decomposition model for the whole sample period and for each half-year separately.[14] The intraday pattern, used to discriminate between expected and unexpected values is updated each half-year. All coefficients have the expected sign, and the coefficients on the order processing component and risk component are always statistically significant. In order to verify the validity of the model, we compare the explanatory power with that of a specification in which the spread is regressed on the input variables to our model, in an ad hoc specification (See Table 5). The R-squared for this specification is considerably lower, and the components are more difficult to interpret. This underlines the value added of the model in understanding the drivers of the bid-ask spread. When comparing the intraday explanatory power of our model with the interdaily analysis by Bollen, Smith and Whaley (2004) on the stock market, we see that it performs slightly weaker, with an R-squared in the range of 30.85%-40.95% where they have an R-squared of 54.40%-80.22% using a similar specification for selective months. They also run an ad-hoc specification, which has an R-squared in the range of 36.99%-57.68%. For the pink sheet market, and using daily data, a linear ad hoc model that incorporates the most-cited explanatory variables for spreads is found to yield an adjusted R-squared of 56% (Bollen and Christie (2009 )).[15] The lower explanatory power for our market could be the result of a lower degree of efficiency in the behaviour of liquidity providers for this minor market, in comparison with the NASDAQ market which is widely followed and has designated market makers.

When we look at the size of the individual cost components, we find that the order processing component accounts on average for 47.09% of the intraday spread. This is in line

[14] We verified whether the results we obtain are possibly spurious by performing an Augmented Dickey-Fuller test on the timeseries of the variables. We can conclude that there is no such risk. Additionally, the value of the Durbin-Watson statistic on the residuals was always found to be bigger than the R-squared of each individual regression.

[15] Pink Sheet stocks do not need to meet certain minimum listing standards, and are traded over-the-counter. As such, information on these stocks is not always available. Stocks are not listed on this market, only quoted.

with other order processing cost estimates for the foreign exchange market using theoretical spread decomposition models: 51% for the NOK/ DEM market (Bjønnes and Rime (2005 )), 45% for the DEM/ USD market (Lyons (1995 )) and 38% for the HUF/ EUR market using a theoretical model for the same sample period (Frömmel and Van Gysegem (2012 )).

We defined the order processing component broad, so that it also includes tick-size. A distinct characteristic of the foreign exchange limit order book we are dealing with is the very low, seemingly irrelevant, tick size. In fact, quotes can in theory be submitted at a resolution up to 0.0001 HUF/EUR. In that sense, tick size could be thought of as being a negligible part of the order processing component. However, if we look to the quotes submitted to the limit order book, the possibility to enter quotes up to such a high resolution is not used by market participants. We rather see the emergence of an endogenous tick size (Bollen and Christie (2009 )). Figure 5 shows the distribution of all best quotes in the book during the two sample years over their first decimal number. We see that quotes like x.4xxx and x.6xxx are less prevalent than x.5xxx, and that quotes like x.9xxx and x.1xxx are less prevalent than x.0xxx. Thus, participants seem to round their quotes at the first decimal level. Figure 6 shows the same distribution for the second decimal. Here it is very clear that the quotes are strongly concentrated on x.x0xx and x.x5xx. Although there is no relevant exchange-mandated tick-size, 0.05 HUF/ EUR emerges as an endogenous tick size (roughly one third of the order processing component). This reflects that the low tick-size is not considered to be optimal. In this context, the tick size does not need to be interpreted as a cost, as is done in some other works, but rather as a (fixed) source of revenues for the liquidity provider.

The expected volume traded is very significant, both in economical and statistical terms. We find that if the expected volume traded is 10% higher (which corresponds to roughly one extra trade at the minimum size above the average), the spread is c.p. 4.50% lower.

We pointed out earlier in this work that liquidity providers will value the risk associated with adding liquidity to the book. We find that our modelled risk component accounts on average for more than half of the spread (52.52%), and is highly significant throughout the half-year periods.[16] So, the combined inventory holding and adverse selection risk clearly explains to a large extent the intraday bid-ask spread. The average volatility throughout the

[16] We verified the robustness of the size of the option component by using a more advanced option valuation method that takes the presence of jumps into account. We therefore apply Merton's mixed jump-diffusion model (Merton, 1976) and use the jump characteristics for this market as reported in Frömmel, Han and Van Gysegem (2013). For the whole sample period, we find that the R-squared only increases slightly (from 34.69% to 34.77%). The risk component becomes slightly more important, and explains in this case 55.81% of the spread instead of 52.52%. The effect remains similar over various subsamples.

dataset is 5.25%. When the volatility is one standard deviation higher, the spread will c.p. be 62.74% higher. We see that the low spread in the last half year (23.90% lower than the two-year average) is caused by a decrease of the risk component: both the size of the costs and the reaction to this cost by the liquidity providers went down. The smaller size of the cost was at its turn caused by a very low volatility and a below average time between two trades.

Bollen, Smith and Whaley (2004) further use the option approach to isolate the adverse selection component. They argue that the relevant option will be out-of-the-money when providing liquidity to an uninformed trader, with the bid (ask) as the strike price for the put (call) option when the liquidity provider accommodates a market sell (buy) order, and the mid-quote as true price. The relevant option will be in-the-money when dealing with an informed liquidity taker with, again, the bid (ask) as the strike price but a true price that is lower (bigger) than the bid (ask) of the put (call) option. This approach, which is very interesting from a conceptual point of view, comes however with a lot of uncertainty. Obviously, the magnitude of the difference between the bid/ ask price and the true price is unknown. Therefore, Bollen, Smith and Whaley (2004) compare this specification for a range of deviations and conclude, based on the explanatory power of the model, that it is most likely between 9% and 12%. Whilst keeping the additional uncertainty in mind, we followed an identical approach. Independent of the deviation we do not find a significant effect, both statistically and economically.

Our results for this further decomposition thus differ from the results for the same dataset when applying a structural spread decomposition methodology. Using this methodology it was found that although it is the smallest cost component, adverse selection costs still account for 21% of the spread (Frömmel and Van Gysegem (2012 )). Bollen, Smith and Whaley (2004) also find clear evidence for an adverse selection component. The difference with their results could lie in the very different market microstructure on the market they study: on the NASDAQ, liquidity is provided by designated market makers (specialists), whereas on our market liquidity is provided endogenously. It could be that this type of liquidity providers does not price adverse selection separately (or to a lesser extent), because the amount of adverse selection on this market is low or because it is difficult to detect. However, as noted above the further decomposition of the risk component comes with a lot of additional uncertainty. Our results could in that sense just be an illustration of this uncertainty.

*Estimate for the number of liquidity providers*

The valuation of the risk component requires information on the time between two trades (See eq. 3). In our dataset we observe all trades together, and are not able to see how long the time between two trades is for an individual liquidity provider. Consequently, we used the average time between two trades as indicator for the time the currencies stay in the inventory of the liquidity provider. Still, the number of liquidity providers active on the market is unknown, but is likely to be higher than one. In that sense, our calculated risk premium is underestimating the risk premium an individual liquidity provider faces: she will have to wait longer before her unwanted inventory is matched with another order. Bollen, Smith and Whaley (2004) show that in these circumstances the number of liquidity providers can be estimated from the data. They argue that in the regression that combines all cost components, the coefficient on the risk component should be one, as liquidity providers are perfectly hedged against this premium. If we then set this coefficient equal to one, we can estimate the length of the holding period:

$$SPRD_i = \alpha_0 + \alpha_1 Exp\,TV_i + RISK_i(t) + \varepsilon_i \qquad \text{(Eq. 5)}$$

With SPRD is the observed intraday spread, Exp TV is the expected volume traded, RISK is the modelled combined inventory holding and adverse selection premium and t is the time between trades.

The estimate for the number of active liquidity providers can be easily calculated: The coefficient $\widehat{\alpha_2}$ from equation 4 can be used as a scaling factor for the average square root of the time between trades. We follow this approach and find that the estimated number of active liquidity providers is 15 for the whole sample period, 27 for the first half of 2003, 10 for the second half of 2003, 17 for the first half of 2004 and 7 for the second half of 2004.[17] The variation over the sample is quite large. The very high number in the first half of 2003 can be explained by the speculative attacks (cf. supra) and the turmoil on the market. We distinguish two different views on the link between the turmoil on the market and the number of liquidity providers we find to be active, depending on how liquidity providers perceived the credibility of the exchange rate band. If they considered the band to be very credible, it was a very interesting time to provide liquidity as they took a very low risk in terms of adverse price

[17] Assuming, naively, that all liquidity are equally actively involved in adding liquidity to the book.

changes (which is basically what the inventory holding cost is about). It can be that this made that more market participants were actively providing liquidity, attracted by the low risk. They later left when the price risk increased again. Alternatively, if they considered the band to be not credible they could have been worried about the risk of big price shifts once the exchange rate breaks through the band. This makes that the inventory holding cost estimate that we obtained using the option model is too low (as the expected volatility was not equal to the ex post measured volatility). The high coefficient on the cost component is in that case not due to a higher number of liquidity providers, but rather to a cost estimate that is not in line with the perceived cost by liquidity providers in the market.

## 6. Applications

The model we developed and used above allows us to analyse the tightness on an intraday basis. In this section we will use it to investigate two interesting spread patterns: the stylized intraday pattern in tightness, and the remarkable spread pattern around a speculative attack against the HUF.

### *6.1. Peak vs. non-peak times*

A first application of the model deals with the analysis of spread components during "peak" and "non-peak" times. It is a well-known fact that many variables related to the activity on a financial market follow an intraday pattern (See for our market Figure 3 and Figure 4). While our results were obtained with data for the most active trading hours (7am till 7pm), there still is a considerable amount of variation in activity over the hours included in our dataset. Based on the intraday distribution of the number of ticks, we are able to define "peak" and "non-peak" times (See Figure 2). We see that from 3pm onwards the activity starts to decline drastically. We will use this as cut-off point, and we will have by consequence 8 intervals per day during peak times and 4 during non-peak times (which results in 4040 observations during peak-times and 2020 observations during non-peak times).

If we look at the difference in spread, there is – as expected – a considerable difference between peak and non-peak times (during non-peak times the spread is more than double as high, see Figure 3). The average spread over the whole sample period during peak times is 0.23 HUF/ EUR, while during non-peak times it is 0.51 HUF/ EUR. Furthermore, we investigate whether this stylized pattern has any relation with the cost components, and if there is a relation, which cost components are responsible for these distinct bid-ask spreads.

For this purpose we introduce a dummy variable for non-peak intervals in the model we applied earlier. The results can be found in Table 6. A first important finding is that compared to peak-times and controlling for the lower volume traded, both constituents of the order processing component are not significantly higher during non-peak times. For the risk component, the picture is different: this component is significantly (in both statistical and economical terms) higher during non-peak times (the coefficient is more than twice as large, the absolute size of the component is almost four times as large). Clearly, both the cost estimate itself and the sensitivity to changes in the calculated cost went up. Taking into account the different behaviour of liquidity providers during non-peak times versus peak-times increases the explanatory power of the model slightly (the R-squared goes from 34.54% to 38.11%).

The total size of the risk component consists of the calculated option premium and its coefficient in the intraday spread regression. First, we elaborate on the causes of the increase in the calculated size of the risk component during non-peak times. There we see that is not the volatility that increased during non-peak times (in fact, over the whole sample period it goes even down from 5.60% during peak times to 4.54% during non-peak times). It is rather the time between two trades that goes up from 9.31 minutes on average during peak-times to 37.80 minutes on average during non-peak times.

Second, we found that the sensitivity to changes in the calculated size of the cost component increases during non-peak times. Obviously, the increasing time between two trades still underestimates the increase in actual risk during non-peak times. At the end of the trading day, it is not only the time the liquidity provider expects her currencies to stay in her inventory that increases. There are two additional costs, which are both related to the risk that the liquidity provider has to keep her position overnight, and will have to wait till the next day in order to unload her inventory. One cost element of holding the inventory overnight is that there is the risk of bigger (adverse) price changes by the time that she starts to trade again the next day. A second element is that she will have to pay an overnight interest rate. Our findings can be related to earlier work that showed that dealers on the foreign exchange market try to end the day (and a fortiori the week) with an empty inventory (Bessembinder (1994); Huang and Masulis (1999 )). It is argued for that matter that this effect is stronger on the foreign exchange market than on the stock market (Bjønnes and Rime (2005 )).

### *6.2. Speculative attacks*

In the data section we referred briefly to the speculative attack against the stronger edge of the Hungarian forint band in January 2003. At this time, the official exchange rate band of the Hungarian central bank was between 234.69 HUF/ EUR and 317.52 HUF/ EUR (276.10 HUF/ EUR ± 15%). In 2002, the government demand increased by 4% of the GDP, which was higher than expected. In the same year, also the wage growth increased more than expected. Both events did put the HUF/ EUR target under pressure. After the referendum on EU enlargement in October 2002, the upward pressure on the HUF/ EUR quote increased even more, because international investors were demanding long-term government securities (convergence trades). Shortly after New Year 2003, there was a growing belief amongst market players that the central bank would have to abandon the exchange rate target. Hedge funds were trying to force a further appreciation of the forint. The central bank, however, intervened on 15 and 16 January 2003, and bought 5.2 billion EUR on the market. After this intervention, the quote moved back inside the band.

We are interested in what role (endogenous) liquidity providers played before, during and after the speculative attack. More specifically we will use the methodology outlined above to analyse the spread set on the market. Figure 9 shows the evolution of the volume traded and the average time-weighted bid-ask spread in a three week timeframe around the speculative attack. We see a very large variation in the bid-ask spread during this timeframe. Interestingly, we find the spread to be gradually decreasing before the attack. The mean spread in the week before the attack was on average 0.13 HUF/ EUR while the average over the whole first half-year of 2003 was 0.32 HUF/ EUR. The attack impacts the quoted spread drastically, and in the week after the attack it is on average 0.53 HUF/ EUR. The build-up towards the attack should have been accompanied by uncertainty about the HUF/ EUR quote, and in that sense the unusually low spread prior to the attack is difficult to understand. Also, the unusually high spread after the attack could have multiple causes. We will investigate them below.

In order to understand how the liquidity provision was impacted by the attack, we apply the model for the three weeks around the attack. We recalculate the coefficients on each component for each week, which allows us to get a precise view on how the behaviour of liquidity providers changed during our timeframe.[18] The results can be found in Table 7. Prior

[18] Here we made the trade-off between having more robust estimates but neglecting the changing dynamics in the weeks around the attack when choosing for longer periods and having not enough observations to draw

to the speculative attack, the absolute order processing component has approximately the same size as the usual order processing component (in this paragraph, we use – given the variation of the results over time (cf. supra) – as usual the average result for the first half-year of 2003). They are respectively 0.1020 HUF/ EUR and 0.1123 HUF/ EUR. So, the low spread clearly stems from a lower risk component which is in absolute size 87.75% lower than usual. Both the value of the cost and the sensitivity to this cost are drastically lower (respectively 67.75% and 62.01% lower). This makes sense if we take into account that when the price is close to the strong band, it can only move in one direction as long as the band is maintained. It is clear that liquidity providers at this stage were not questioning the credibility of the band, and were considering the risk of adverse price changes to be much lower than usual.

In the week of the speculative attack, the spread rises with 42.85%. Still, the absolute order processing component decreases by 52.84%. Possible reason could here be that more participants start to follow the market very closely in the run-up to the attack. The increased competition that results from this erodes the fixed component of the spread (which also contains competitive rents, as argued earlier in the paper). Here the absolute size of the order processing component (0.0481 HUF/ EUR) becomes even slightly smaller than the endogenous tick size we found (0.05 HUF/ EUR). Key to understanding what drives the spread is here, again, the risk component: both the sensitivity to the cost and the cost itself increase greatly (respectively by 131.00% and by 128.68%). The increase in sensitivity can be linked to the increased competition that already affected the order processing component (when more liquidity providers are active, the difference between the average time between two trades on the market and the average time between two trades for an individual liquidity provider becomes bigger). The increase in the cost itself stems from the very high volatility during this week. The combined effect makes that the risk component is more than four times larger than the risk component in the week before the attack.

In the week after the attack, the spread is more than three times higher than in the week before this extreme event. Clearly, the fact that the attack actually happened made the market less tight and therefore illiquid, even if the central bank intervened successfully directly after the attack. The higher spread after the attack stems from an increase in both the order processing and the risk component compared to the pre-attack week. The order processing component and sensitivity to the order processing cost increased. Both could be explained by reduced competition after the attack. Additionally, the calculated risk component also went up

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reasonable conclusions from our regressions but having a potentially more detailed view on the dynamics when opting for shorter periods.

by 353.49%. This is clearly the effect of the unusually low volatility that has been replaced by unusually high volatility. The sensitivity to the risk component almost doubled compared to the pre-attack week: now the quote can again move in two directions (as it shifted inside the band). Consequently, accommodating orders becomes more risky for liquidity providers, and they do ask a compensation for this.

Using the weekly coefficients, we also calculate the estimated daily spread components during the three weeks around the attack. Figure 10 shows the resulting components and the observed spread per day. We see that the model is able to track the day-to-day dynamics of the quoted spread. Figure 10 further illustrates how the order processing costs and risk component are driven by conditions on the market (number of liquidity providers/ competition, (un)certainty, market activity), and how this is directly reflected in the quoted spread.

## 7. Summary

In this work, we applied an empirical spread decomposition model to the HUF/ EUR market. Our data covers the complete electronic interbank market –where the price formation takes place– for a timespan of two years. We use intraday data coming from a tick-by-tick database and the reconstructed limit order book.

We examine the costs of providing liquidity in this type of market, and briefly summarize how these costs are treated in related literature. In a second step, these costs are quantified and the model is applied. We find that order processing accounts for 47.09% and the combined risk component accounts for 52.52% of the quoted spread. Over our sample period, we see a considerable amount of variation in their size. Although there is no exchange-mandated tick size, we do find evidence for an endogenous tick size of 0.05 HUF/ EUR. This tick size represents roughly one third of the order processing costs. The combined inventory holding and adverse selection risk is modelled as an option, and the costs are sized using option valuation. We can confirm that the option based model performs better than an ad hoc specification. We also find that the sensitivity of liquidity providers to the option value varies over time. We can partially explain this variation by a changing number of liquidity providers. When we try to split up the risk component further into a separate inventory holding and adverse selection component, we cannot find evidence for adverse selection. This is in contrast with existing NASDAQ results.

We further examine two interesting cases. During non-peak times, the spread is more than twice as high as during peak times. We use our model to investigate this discrepancy in more detail, and find that it is especially a higher risk component that is the cause. When we elaborate on this, we see that the average time between two trades increases but that liquidity providers are also concerned about the risk that they will have to carry their unwanted inventory overnight.

We also detect an interesting spread pattern around a speculative attack. As a second application, we study the dynamics of the cost components around this attack. We find an extremely high willingness to provide liquidity prior to the attack which results from the low risk component prior to the attack. During the attack, the risk component obviously increases and the order processing costs go down, which could be the result of increasing competition amongst liquidity providers. After the attack and the intervention by the central bank spreads rise massively. Now, both components go up: order processing costs rise again, and a strong increase in volatility makes that the inventory holding costs go up.

Overall, this paper demonstrates the relevance of an option based spread decomposition approach for understanding how liquidity is provided on an interbank foreign exchange market. An interesting avenue for further research would be to employ data at the level of individual liquidity providers to study the heterogeneity amongst them and measure the ex post risk of holding an inventory. These findings could then further be integrated in a refined model of liquidity provision.

## FIGURES

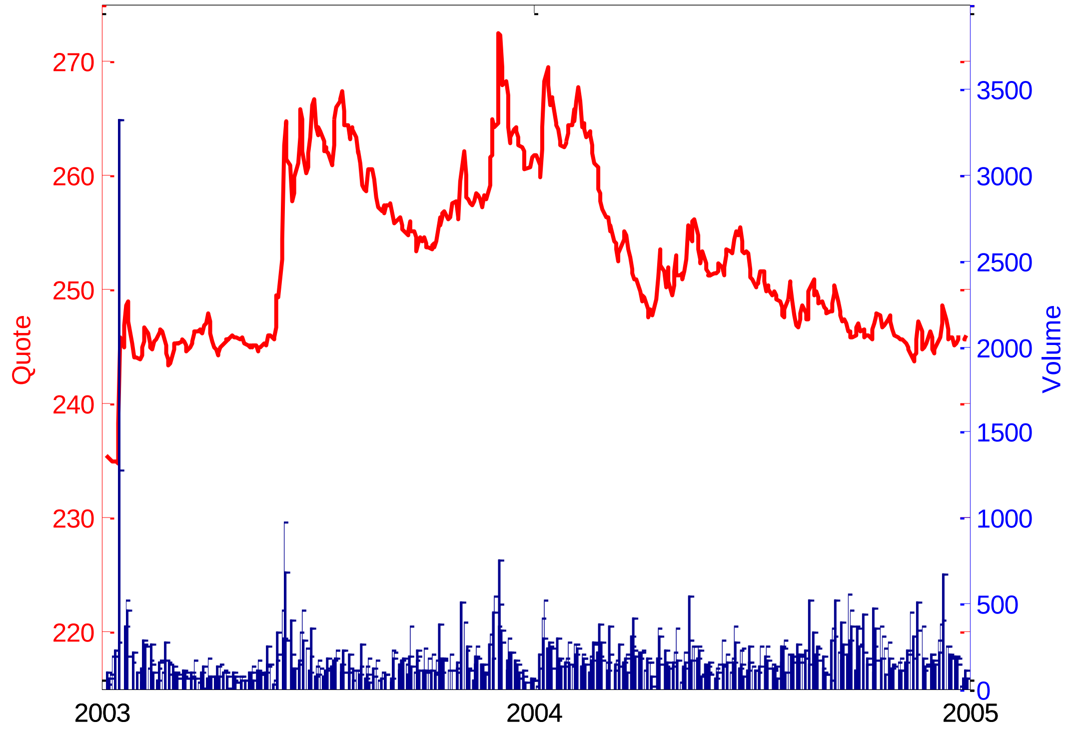


**Figure 1: Average daily quote and total volume traded over the sample period**

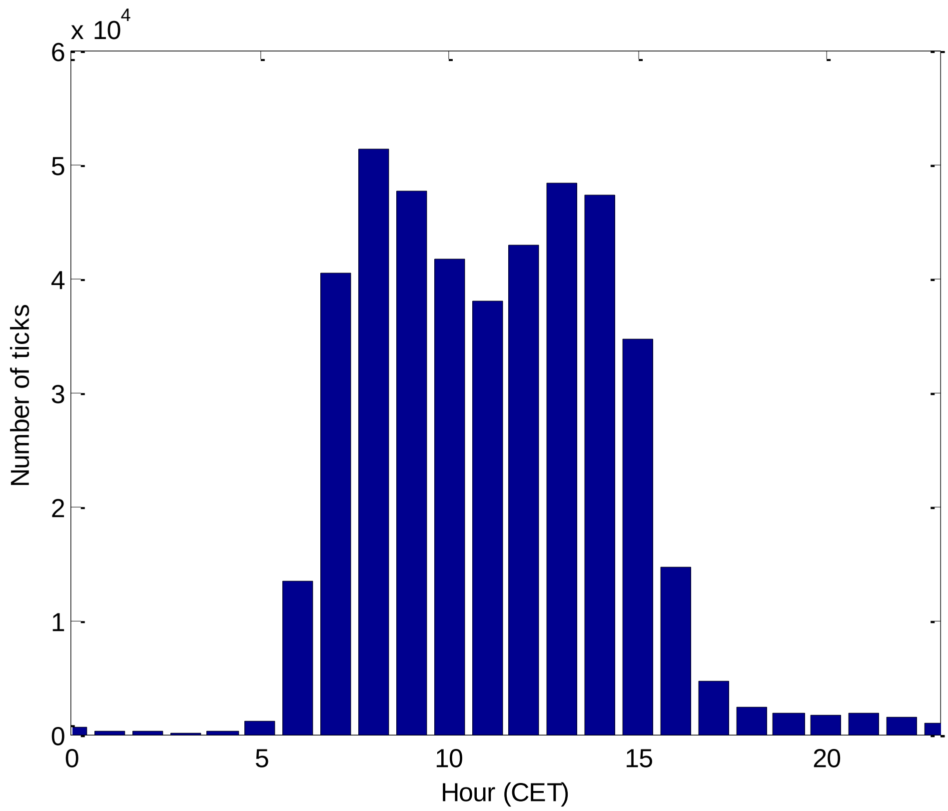


**Figure 2: Number of ticks per hour (CET).**

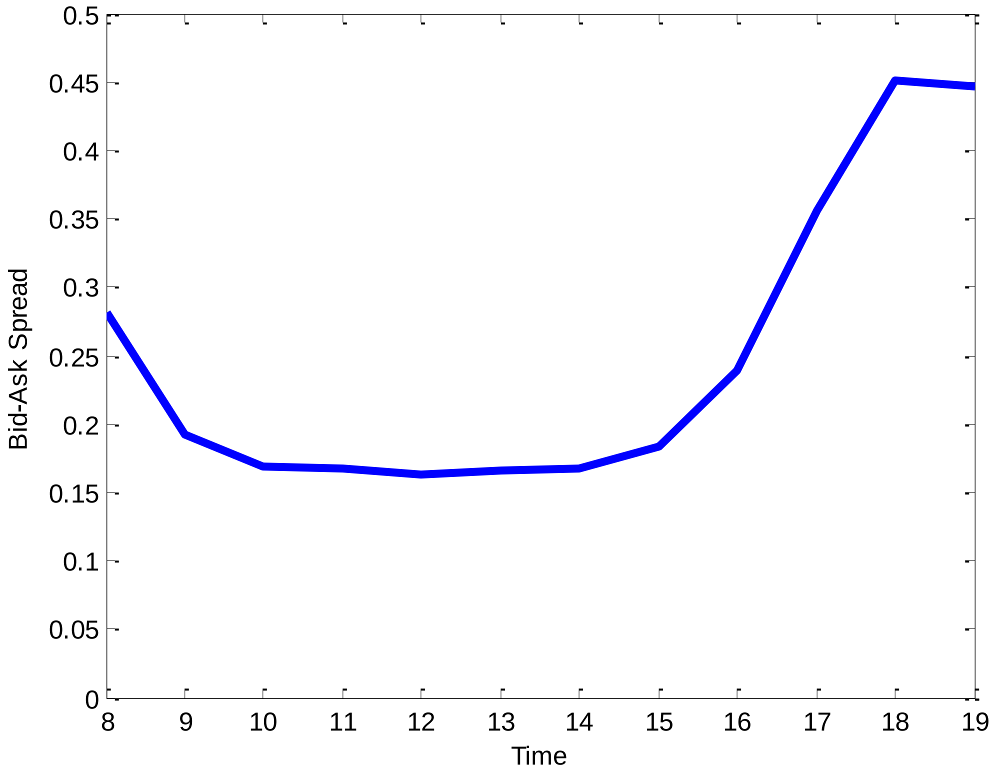


**Figure 3: Expected bid-ask spread (HUF/ EUR; Intraday median)**

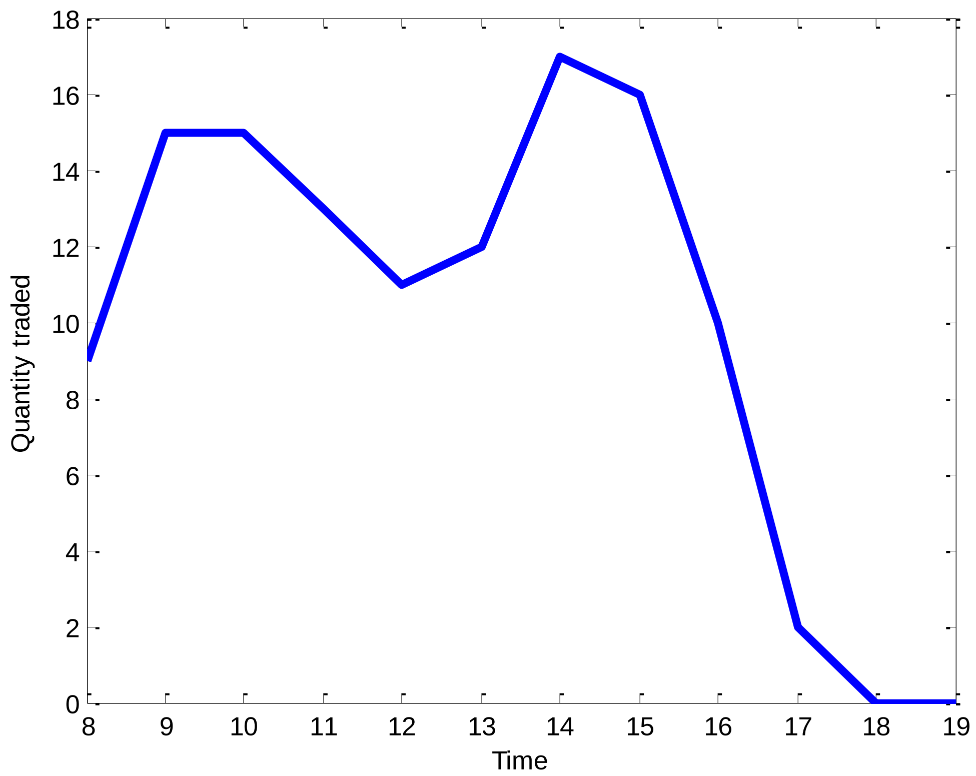


**Figure 4: Expected quantity traded (Mill HUF; Intraday median)**

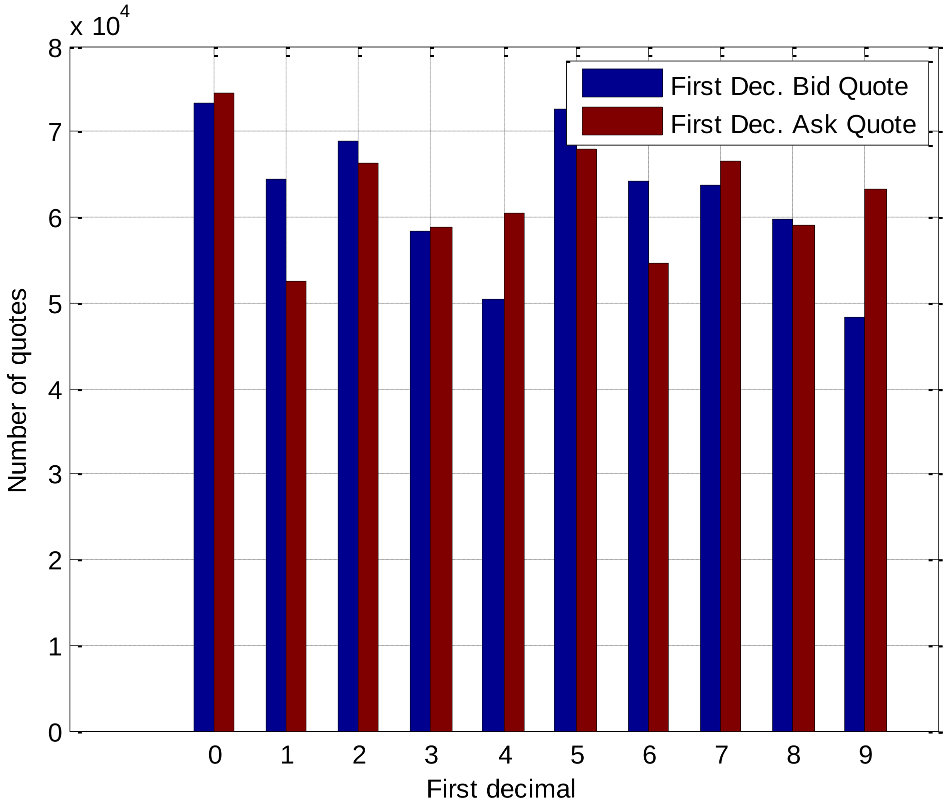


**Figure 5: First decimal number of best bid/ best ask (HUF/EUR)**

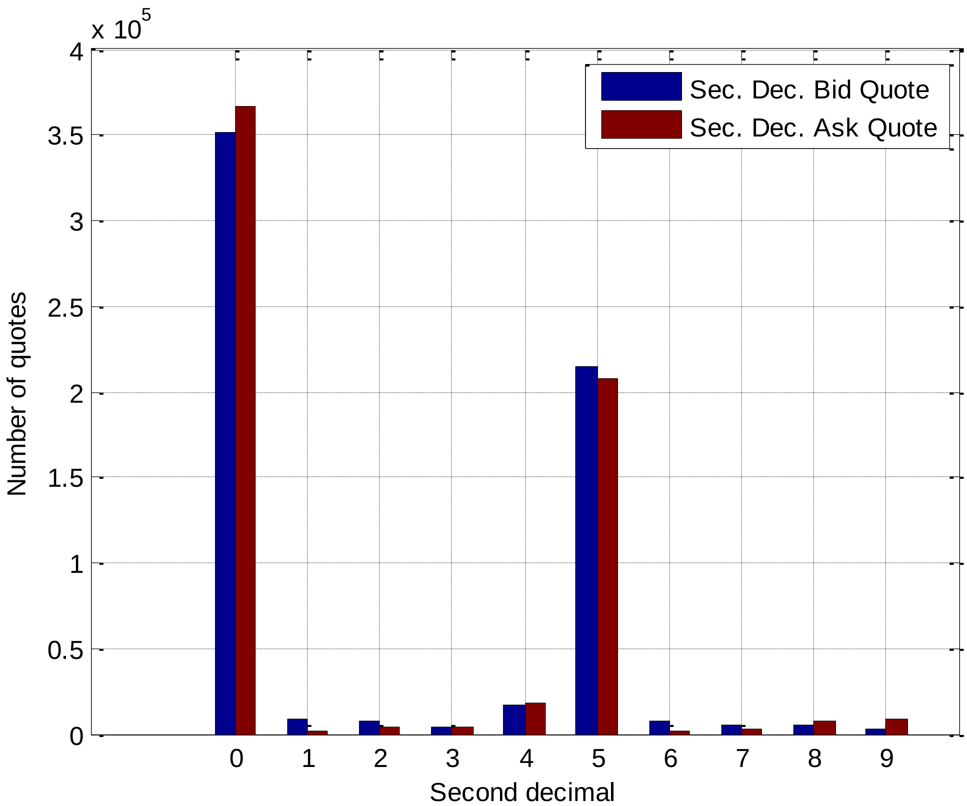


**Figure 6: Second decimal number of best bid/ best ask (HUF/ EUR)**

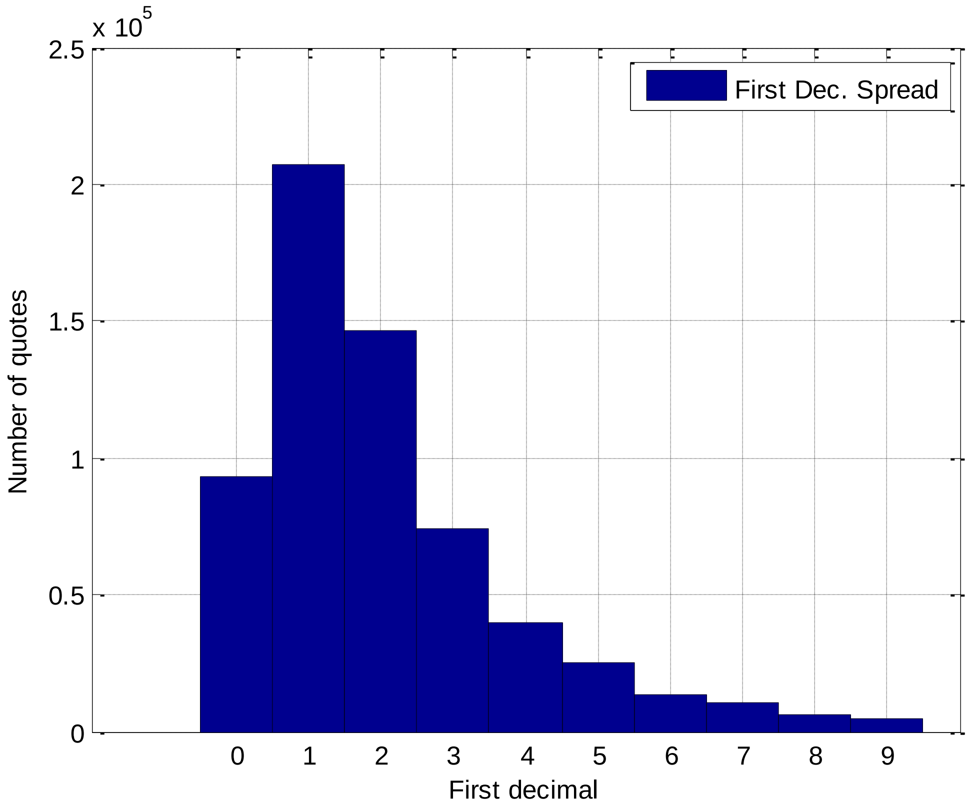


**Figure 7: First dec. bid-ask spread (HUF/ EUR)**

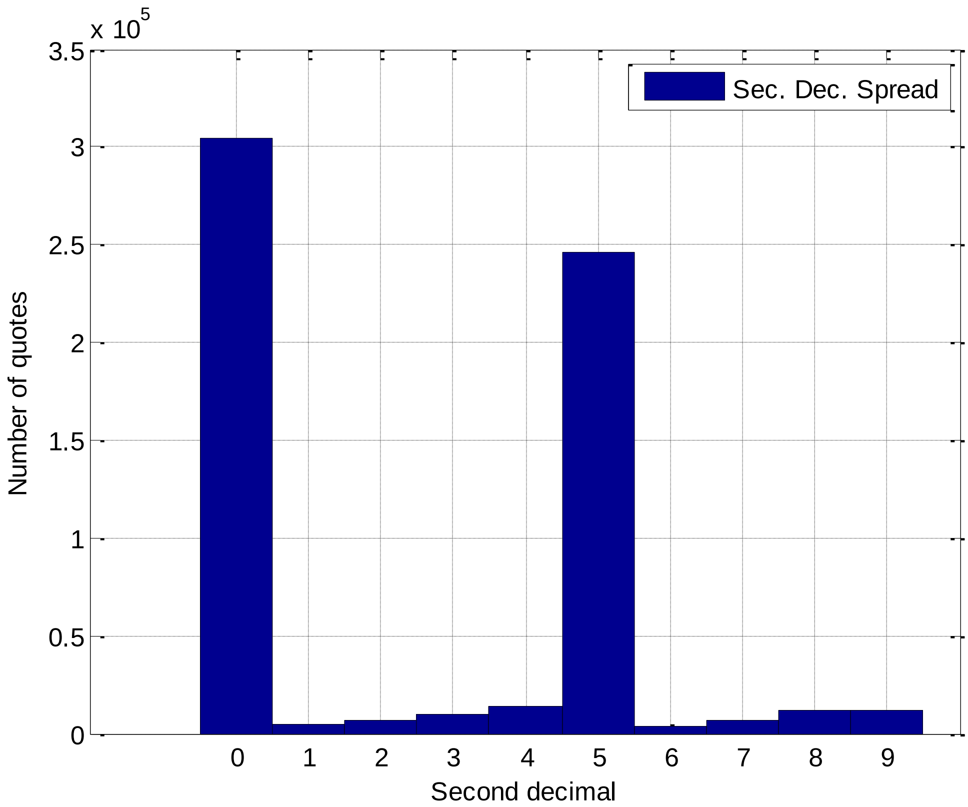


**Figure 8: Second dec. bid-ask spread (HUF/ EUR)**

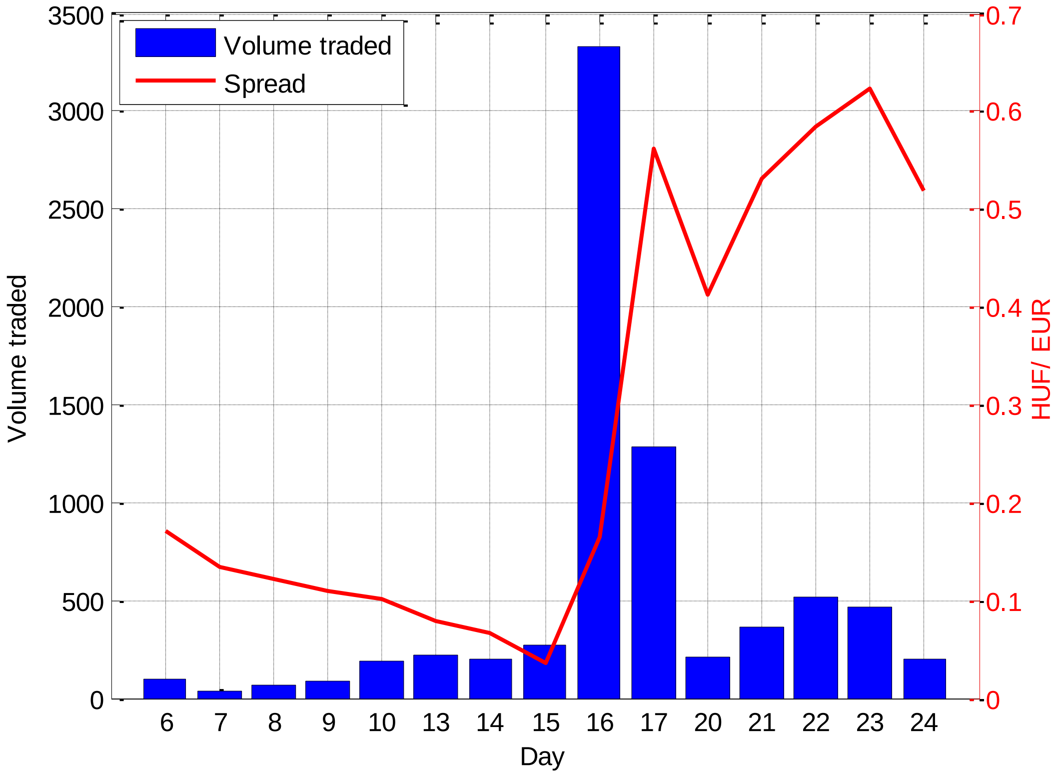


**Figure 9: Spread and volume traded around the speculative attack**

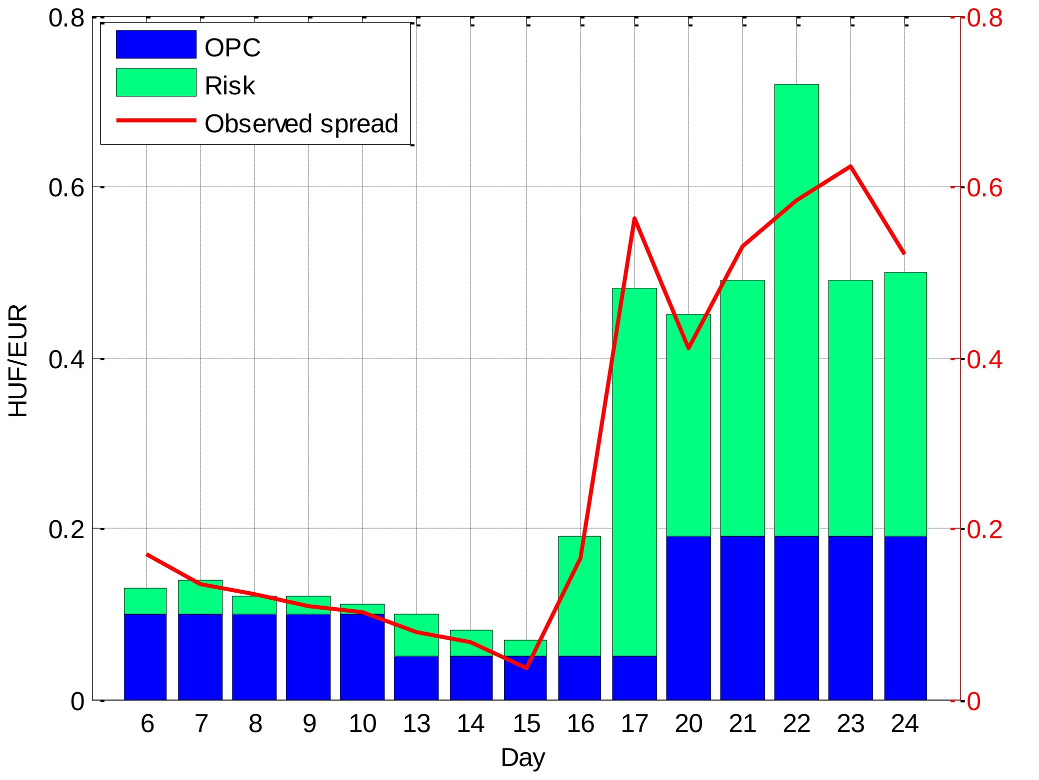


**Figure 10: Spread components around the speculative attack (January 2003)**

## TABLES

| | Whole sample | 2003 | 2004 |
|---|---|---|---|
| **Number of quotes** | 437,420 | 193,447 | 243,973 |
| **Number of trades** | 72,622 | 31,978 | 40,644 |
| **Average trade size** | 1,304,398 EUR | 1,339,827 EUR | 1,276,523 EUR |
| **Trades ≤ 1 million €** | 80.38% | 78.89% | 81.55% |
| **Trades >1 million € and <3 million €** | 13.79% | 14.50% | 13.23% |
| **Trades ≥ 3 million €** | 5.83% | 6.61% | 5.22% |
| **Average number of quotes per day** | 881.90 | 806.03 | 953.02 |
| **Average number of trades per day** | 146.42 | 133.24 | 158.77 |
| **Average daily trading volume (million €)** | 190.98 | 178.52 | 202.67 |

**Table 1: Summary statistics**

**Distribution of regression variables**

| | 25% | Median | 75% | Mean |
|---|---|---|---|---|
| **Quoted Spread (time weighted average)** | 0.15 | 0.21 | 0.34 | 0.32 |
| **Quoted Spread (last observation)** | 0.13 | 0.20 | 0.35 | 0.34 |
| **Volume Traded (million EUR)** | 2 | 9 | 20 | 16 |
| **Expected Volume Traded (million EUR)** | 6.25 | 12 | 15 | 10.19 |
| **Mid-Quote (time weighted; HUF/ EUR)** | 246.13 | 251.14 | 258.11 | 252.59 |
| **Volatility** | 2.24% | 3.83% | 6.11% | 5.25% |
| **Intra-Trade Time (minutes)** | 3 | 6.67 | 30 | 18.80 |

**Mean of regression variables over time**

| | 2003 Jan-Jun | 2003 Jul-Dec | 2004 Jan-Jun | 2004 Jul-Dec |
|---|---|---|---|---|
| **Quoted Spread (time weighted average)** | 0.32 | 0.39 | 0.35 | 0.25 |
| **Quoted Spread (last observation)** | 0.32 | 0.39 | 0.39 | 0.25 |
| **Volume Traded (million EUR)** | 15.96 | 13.86 | 16.08 | 18.04 |
| **Expected Volume Traded (million EUR)** | 7.58 | 9.08 | 11.88 | 12.08 |
| **Mid-Quote (time weighted; HUF/ EUR)** | 247.26 | 259.80 | 256.02 | 247.32 |
| **Volatility** | 5.21% | 6.08% | 5.85% | 3.90% |
| **Intra-Trade Time (minutes)** | 21.86 | 19.64 | 16.55 | 17.30 |

**Table 2: Summary statistics of the variables used in the regression**

| | Spread (time weight.) | Spread (latest) | Volume (expected) | Volume (unexpected) | Volatility | Time btwn. trades | Option |
|---|---|---|---|---|---|---|---|
| **Spread (time weight.)** | **1.00** | 0.34 | -0.35 | -0.05 | 0.23 | 0.38 | 0.56 |
| **Spread (latest)** | 0.34 | **1.00** | -0.13 | -0.01 | 0.07 | 0.14 | 0.18 |
| **Volume (expected)** | -0.35 | -0.13 | **1.00** | 0.06 | 0.04 | -0.67 | -0.30 |
| **Volume (unexpected)** | -0.05 | -0.01 | 0.06 | **1.00** | 0.29 | -0.26 | -0.12 |
| **Volatility** | 0.23 | 0.07 | 0.04 | 0.29 | **1.00** | -0.14 | 0.60 |
| **Time btwn. trades** | 0.38 | 0.14 | -0.67 | -0.26 | -0.14 | **1.00** | 0.43 |
| **Option** | 0.56 | 0.18 | -0.30 | -0.12 | 0.60 | 0.43 | **1.00** |

**Table 3: Correlation matrix**

| Period | Statistic | Mean Quoted Spread | Order Proc. Comp. | | Risk Comp. | $R^2$ |
|---|---|---|---|---|---|---|
| | | | Constant | E[Vol. Traded] | | |
| **2003-2004** | Coefficient | | 0.2920 | -0.0137 | 3.9302 | |
| | (t-statistic) | | (8.95) | (-10.97) | (7.07) | |
| | Mean | 0.3246 | | 10.1868 | 0.0434 | 34.69% |
| | Abs. Size Comp. | | **0.1529** | | **0.1705** | |
| | Rel. Size Comp | | **47.09%** | | **52.52%** | |
| **2003 Jan-Jun** | Coefficient | | 0.2473 | -0.0178 | 5.1544 | |
| | (t-statistic) | | (4.88) | (-7.99) | (4.65) | |
| | Mean | 0.3185 | | 7.5833 | 0.0400 | 40.95% |
| | Abs. Size Comp. | | **0.1123** | | **0.2064** | |
| | Rel. Size Comp. | | **35.26%** | | **64.80%** | |
| **2003 Jul-Dec** | Coefficient | | 0.4111 | -0.0205 | 3.1225 | |
| | (t-statistic) | | (10.10) | (-8.38) | (6.38) | |
| | Mean | 0.3899 | | 9.0833 | 0.0528 | 30.85% |
| | Abs. Size Comp. | | **0.2251** | | **0.1648** | |
| | Rel. Size Comp. | | **57.74%** | | **42.26%** | |
| **2004 Jan- Jun** | Coefficient | | 0.3021 | -0.0134 | 4.1700 | |
| | (t-statistic) | | (3.81) | (-4.70) | (3.60) | |
| | Mean | 0.3453 | | 11.8750 | 0.0486 | 33.75% |
| | Abs. Size Comp. | | **0.1428** | | **0.2025** | |
| | Rel. Size Comp. | | **41.35%** | | **58.65%** | |
| **2004 Jul-Dec** | Coefficient | | 0.3007 | -0.0118 | 2.5738 | |
| | (t-statistic) | | (5.53) | (-5.75) | (2.38) | |
| | Mean | 0.2470 | | 12.0833 | 0.0324 | 35.17% |
| | Abs. Size Comp. | | **0.1584** | | **0.0833** | |
| | Rel. Size Comp. | | **64.11%** | | **33.73%** | |

**Table 4: Regression results and spread components.**

**The option value was calculated under the assumption that there is one liquidity provider - the patterns were updated each half year - all t-statistics are corrected for heteroskedasticity**

| Statistic | Constant | E[Vol. Traded] | Intra-trade time | Volatility | $R^2$ |
|---|---|---|---|---|---|
| **Coefficient** | 0.2085 | -0.0106 | 58.6324 | 2.1611 | 23.53% |
| **(t-statistic)** | (8.08) | (-9.97) | (12.10) | (7.44) | |
| **Mean** | | 10.1868 | 0.0019 | 0.0525 | |
| **Average share in average spread size** | 64.23% | -33.32% | 34.32% | 34.95% | |

**Table 5: Regression with ad hoc specification**

**The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity**

| Timing | Statistic | Mean Quoted Spread | Order Proc. Comp. | | Risk Comp. | $R^2$ |
|---|---|---|---|---|---|---|
| | | | **Constant** | **E[Vol. Traded]** | | |
| **Peak** | Coefficient | | 0.2155 | -0.0054 | 2.5428 | 37.93% |
| | (t-statistic) | | (7.52) | (-5.52) | (4.02) | |
| | Mean | 0.2305 | | 13.70 | 0.0343 | |
| | Abs. Size Comp. | | **0.1416** | | **0.0872** | |
| | Rel. Size Comp | | **61.41%** | | **37.84%** | |
| **Non-peak** | Coefficient | | 0.2257 | -0.0110 | 5.2225 | |
| | (t-statistic) | | (0.16) | (-1.90) | (2.50) | |
| | Mean | 0.5096 | | 3.17 | 0.0616 | |
| | Abs. Size Comp. | | **0.1909** | | **0.3217** | |
| | Rel. Size Comp. | | **37.46%** | | **63.13%** | |

**Table 6: Spread components during peak and non-peak times**

**The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity**

| Timing | Statistic | Mean Quoted Spread | Order Proc. Comp. | | Risk Comp. | $R^2$ |
|---|---|---|---|---|---|---|
| | | | **Constant** | **E[Vol. Traded]** | | |
| **Week before attack (6-10/01)** | Coefficient | | 0.1713 | -0.0091 | 1.9581 | |
| | (t-statistic) | | (8.99) | (-6.26) | (1.74) | |
| | Mean | 0.1272 | | 7.58 | 0.0129 | 48.98% |
| | Abs. Size Comp. | | **0.1020** | | **0.0253** | |
| | Rel. Size Comp | | **80.15%** | | **19.85%** | |
| **Week of attack (13-17/01)** | Coefficient | | 0.1018 | -0.0071 | 4.5233 | |
| | (t-statistic) | | (1.93) | (-1.31) | (5.90) | |
| | Mean | 0.1817 | | 7.58 | 0.0295 | 59.87% |
| | Abs. Size Comp. | | **0.0481** | | **0.1336** | |
| | Rel. Size Comp. | | **26.48%** | | **73.52%** | |
| **Week after attack (20-24/01)** | Coefficient | | 0.4830 | -0.0383 | 5.8272 | |
| | (t-statistic) | | (3.45) | (-3.78) | (4.69) | |
| | Mean | 0.5338 | | 7.58 | 0.0585 | 54.35% |
| | Abs. Size Comp. | | **0.1929** | | **0.3409** | |
| | Rel. Size Comp. | | **36.13%** | | **63.87%** | |

**Table 7: Spread components around speculative attack**

**The patterns were updated each half year - all t-statistics are corrected for heteroskedasticity**

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