Commonality in equity options liquidity: Evidence from NYSE LIFFE

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Abstract

This paper examines the commonality in liquidity for individual equity options trading at NYSE LIFFE. We use high-frequency data to construct a novel index of liquidity commonality and we find that it can explain a substantial proportion of the liquidity variation of individual options. The explanatory power of the common liquidity factor is more pronounced during periods of higher implied volatility at the market level. The common factor's impact on individual options' liquidity is found to depend on the options' idiosyncratic characteristics, while there is limited evidence of systematic liquidity spillover effects among the NYSE LIFFE exchanges.

JEL Classifications: G12; G19

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1. Introduction

The issue of liquidity underpins virtually every financial transaction and it has been attracting increasing attention in the literature, especially after the recent financial crisis. One particularly important aspect of this issue refers to the role of common cross-asset variation in liquidity. To the extent that liquidity across assets is driven by common factors, understanding the behavior of liquidity's systematic component is

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fundamental in explaining, and ultimately anticipating, incidents of a general liquidity breakdown. The recent financial crisis serves as an illustrative example of the dramatic impact that a break in systematic liquidity can have on global financial markets, as do the stock market crisis of 1987 and the debt market crisis of 1998 which are typically viewed as systematic liquidity breakdowns (Hasbrouck and Seppi, 2001). In this paper, we examine the systematic liquidity component extracted from a large high-frequency dataset of equity options traded in NYSE LIFFE.

Previous empirical studies have highlighted the existence of a common liquidity factor across individual assets (Cao and Wei, 2010; Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001). One likely explanation for this commonality in liquidity could be related to inventory management considerations. In particular, market-wide swings in prices and/or volatility are expected to affect trading volume, which is one of the principal determinants of dealer inventory. As a result, dealers are likely to respond by changing their optimal levels of inventory across assets in a relatively uniform way, affecting the provision of liquidity (for example as it is reflected by quoted spreads and depths). Another possible source of liquidity commonality is the fact that market rates have a direct impact on the dealers' cost of carrying inventory (see also Chordia et al., 2000).

Irrespective of its sources, commonality in liquidity has important implications for market participants. For instance, the common component of asset liquidity potentially represents an undiversifiable source of price risk which, in equilibrium, should be priced in the cross-section of expected returns (Brennan and Subrahmanyam, 1996; Chordia et al., 2000). More importantly, temporary large changes in this common liquidity factor are likely to trigger incidents of market stress which could, even in the absence of other significant events, precipitate a financial crisis. For example, the October 1987 stock market crash was characterized by a dramatic drop in liquidity although it is hard to identify any concurrent significant financial events (Roll, 1988).

This paper contributes to the literature in a number of ways. First, we expand the literature on liquidity commonality to a new market, namely the European market of NYSE LIFFE. Previous studies on commonality in liquidity have predominantly focused on stock markets. For instance, Chordia et al. (2000) construct a systematic liquidity factor and explore the extent to which it can explain individual liquidity across stocks (see also Brockman and Chung, 2002, 2006; Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008). Furthermore, Kempf and Mayston (2008), Rakowski and Beardsley (2008) and Visaltanachoti et al. (2008) examine liquidity commonality along the order book, while Dunne et al. (2011) document substantial common movements in returns, order flows and liquidity for the Athens Stock Exchange. Despite the significant interest in liquidity commonality for stocks, this issue has remained relatively underexplored in the case of options.[1] Cao and Wei (2010), who extract a common liquidity component for US options, represent the main exception. We contribute to the related literature by investigating liquidity commonality in the largest options market in Europe. Combining the exchanges of Amsterdam, London and Paris, NYSE LIFFE accounts for a large part of global exchange-based trading in options and, as such, its systematic liquidity component is likely to have a substantial impact on investors internationally.[2]

Second, we contribute to the literature by examining what drives systematic liquidity. More specifically, we investigate how commonality in liquidity behaves under different market conditions by examining its relationship with a set of market-wide factors such as index options' trading volume and implied volatility, a sentiment indicator, short sale restrictions, and momentum factors for past returns. We also investigate if the explanatory power of liquidity commonality over a given option's individual liquidity depends on the option's idiosyncratic characteristics (e.g. market value, volatility, underlying stock's spread etc.). Finally, we explore potential spillover effects among the three options exchanges of NYSE LIFFE.

Our third contribution relates to the use of high-frequency options data. Previous studies have used daily data to compute liquidity measures. In contrast, we extract our liquidity commonality factor from an extensive high-frequency dataset of options, which allows us to obtain considerably more accurate measures of liquidity by taking into account the intraday variation in trading activity.

We employ Principal Component Analysis (PCA) to extract the common liquidity factor. Our results highlight that common effects are significant drivers of options liquidity in NYSE LIFFE. More specifically, we report that the proportion of variance explained by the common liquidity factor in the PCA is 15% for Amsterdam, and 27% for London and Paris. When we regress the liquidity of individual options against the first common factor from the PCA, we find that the latter can explain on average 11% of the

[1] In contrast to the very limited interest in commonality in options liquidity, some previous studies have investigated the determinants of options liquidity. For instance, Cho and Engle (1999) link liquidity in the options market to the activity of the underlying market through the derivatives hedging theory, while Wei and Zheng (2010) associate market liquidity with inventory management practices.

[2] Verousis et al. (2015) also examine liquidity for options traded in NYSE LIFFE. However, they focus on the intraday determinants of liquidity for individual options, with only a brief mention of a common factor. In contrast, this paper shifts the emphasis from idiosyncratic characteristics acting as liquidity determinants to exclusively examining commonality in liquidity as the driving factor.

liquidity variance at the ticker level, with this proportion rising to 15% when we use the first three common factors.

Moreover, the explanatory power of commonality in liquidity over the liquidity of individual options appears to depend on market conditions. When we regress the proportion of liquidity variance at the ticker level that can be explained by the common liquidity component against a set of market-wide factors, we find that the strongest effect stems from the index's implied volatility. In particular, on days of greater uncertainty at the aggregate market level, as reflected by higher levels of index implied volatility, systematic liquidity has a bigger contribution to the liquidity of individual options. The explanatory power of the common factor generally correlates with the sign of market returns in the case of calls, and it is also related to market trading volume and sentiment for Amsterdam in particular, where retail activity is highest.

We document that the extent to which individual options' liquidity responds to systematic liquidity depends on the characteristics of the options and those of the underlying stocks. In cross-sectional regressions, we find that the common factor's explanatory power over the liquidity variance of individual options is significantly positively related to the frequency of transactions and negatively related to trading volume and options' realized volatility. In other words, options with a larger number of relatively low-volume transactions at low levels of volatility appear to be more responsive to the common liquidity factor compared to their counterparts. The underlying's percentage bid-ask spread is found to positively affect the explanatory power of the common factor for puts, while the firm's market value has a significantly positive effect in the case of calls.

Finally, using a Vector Autoregression (VAR) framework, we find some interconnectedness among the three exchanges of NYSE LIFFE in terms of systematic liquidity's explanatory power over individual options' liquidity. However, these spillover effects do not appear to be particularly pronounced.

The remaining of the paper is organized as follows. Section 2 discusses the market structure of NYSE LIFFE and the high-frequency options dataset used in the empirical analysis. Section 3 describes the methodology for extracting the liquidity commonality factor, variable construction and research design. Section 4 presents the empirical results, while Section 5 concludes.

2. Market Structure and Data

2.1 Market Structure

NYSE LIFFE represents the European branch of NYSE for derivatives trading, consisting of five country-specific exchanges, namely Amsterdam, Brussels, Lisbon, London and Paris. In this paper, we examine the liquidity of individual equity options in Amsterdam, London and Paris, since options are not traded in Lisbon and option trading is very limited in Brussels.

Options trading in NYSE LIFFE is structured around market makers who provide liquidity under the Euronext Liquidity Provider System (ELPS), by continuously submitting bid and asks quotes. The ELPS, which sets the various spread and size obligations for market makers' quotes across different contracts, was initially introduced in Amsterdam and subsequently adopted for all options contracts traded via LIFFE CONNECT.

The market makers who operate in NYSE LIFFE fall under two general categories, depending on the extent of their contractual obligations to the exchange. More specifically, Primary Liquidity Providers (PLPs) are required to submit quotes for In-The-Money (ITM) and Out-of-The-Money (OTM) contracts, while Competitive Liquidity Providers (CLPs) need to submit quotes only for a number of near-the-money contracts.[3] The classification of market makers is somewhat different in Amsterdam, where Primary Market Makers (PMMs) are required to provide bid and asks for all individual equity options across all strikes and maturities, while Competitive Market Makers (CMMs) have contractual obligations similar to those of CLPs.[4]

Market makers' obligations in terms of submitting quotes refer to both a maximum spread and a minimum size and they vary across different underlying assets, since they are set out as functions of the underlying's price and volatility (updated semi-annually). Furthermore, market makers are required to submit continuous quotes for a minimum of 85% of the contracts in the series in which they are involved, and at least during 85% of the specific time period. Finally, all market makers have to trade at least a minimum number of contracts of the highest liquidity assets, as these are defined by the exchange.

Despite a significant effort to harmonize rules across the number of exchanges of NYSE LIFFE, several important differences remain. First, the options exchange in Amsterdam is at the cutting edge of high frequency trading (HFT), with Dutch firms

[3] "Near-the-money" refers to a flexible concept, defined as a percentage mark up (down) from the lowest (highest) underlying share price of the current day.
[4] PMMs may also have the right to receive a percentage of the turnover traded at the PMM's best bid or ask price. CMMs and PMMs may quote spreads up to twice the maximum contractually agreed spread.

contributing three of the four founding members of the HFT body for Europe (The Economist, 2013). Second, the Premium Based Tick Size (PBTS) rule that was implemented in Amsterdam is expected to have a significant impact on the exchange's liquidity, particularly with respect to increasing the liquidity of lower-priced options. Third, the number of market makers whose role is to provide liquidity has not been harmonized across exchanges. Finally, the extent to which individual investors participate in options trading exhibits substantial variation across the three options exchanges of NYSE LIFFE.

2.2 Data

Our objective is to construct daily time-series of liquidity and volatility measures that incorporate the rich information available from intraday data (see also Stoll, 2000, who uses an intraday dataset across 61 trading days for 3,890 NYSE stocks and 2,184 NASDAQ stocks). Our dataset consists of tick data for all options written on individual stocks (henceforth referred to as tickers) that traded on NYSE LIFFE Amsterdam, London and Paris from March 2008 to December 2010.[5] This intraday options dataset covers a period of 34 months in total, which is substantially long by the standards of the related high-frequency literature. Each ticker consists of several sub-tickers, i.e. option contracts that are written on the same underlying stock but have different characteristics in terms of strike price, time-to-maturity and contract type (call or put). The dataset includes, among other fields, the option price, strike price, maturity date and volume for every sub-ticker, time-stamped to the nearest second. This information is provided separately for asks, bids and trades.

We follow Stoll (2000) to construct daily time-series for each ticker using the high-frequency dataset, in order to obtain more accurate estimates of daily liquidity across a relatively large sample (the number of trading days per ticker ranges from 707 to 712). For each exchange, we categorize sub-tickers according to their type (call or put), moneyness level (defined as the ratio of the underlying's opening price S to the option's strike price K) and time-to-maturity.[6] Furthermore, we focus only on Short-Term (ST) At-The-Money (ATM) contracts, selecting sub-tickers that are within 90 days to expiration (but not expiring in the next 7 days) and with a spot-to-strike ratio S/K between 0.95 and 1.05.

[5] The number of tickers refers to the total number of underlying assets on which options have been written trading at the exchanges (firm-options), including delisted options.
[6] End-of-day prices for the underlying stocks were obtained through DataStream.

In addition to selecting option contracts according to their moneyness and time-to-maturity, several other filters are applied to the intraday dataset. First, we drop tickers for which we cannot find the respective underlying assets in DataStream. Second, we drop all European-style contracts trading in Paris (leaving only American-style options in our sample) as well as the newly introduced contracts with weekly and daily expirations trading in Amsterdam (to avoid short-expiration effects). Third, we address the potential issue of misrecordings by deleting observations with zero volumes, zero prices, negative or zero bid-ask spreads, and out-of-hours time-stamps.[7] Finally, we follow Wei and Zheng (2010) to delete observations with exceptionally large bid-ask spreads (exceeding 150% for ATM contracts). As can be seen from Table 1, the majority of contracts are kept post filtering, with 90%, 93% and 84% of observations maintained for Amsterdam, London and Paris, respectively.

3 Methodology

3.1 Variable Construction

We compute spreads and returns of option sub-tickers as the mid-points of bids and asks sampled at 5-minute intervals. More specifically, on each trading day, we begin by identifying the first quote of the day (which is provided by 8:01 at the latest) and then split the trading day to 5-minute intervals (n = 101 intervals within a trading day). Moreover, we enforce a 2-minute rule for the closing interval (16:30) and we also control for stale pricing by dropping quotes that are recorded more than 2 minutes prior to each interval. We record the bids and asks for each 5-minute interval and compute midquotes when both bids and asks are available for a particular interval, otherwise the midquote is treated as a missing observation. This approach allows us to construct observations at the maximum number of intervals, after addressing potential biases of missing variables and stale pricing.

Similarly to Frino et al. (2008) and Mayhew (2002), we compute volume-weighted and price-volume-weighted quoted spreads, in order to account for the fact that spreads vary with the price level. The volume-weighted quoted spread *VolSpr* and the price-volume-weighted quoted spread *PVolSpr* for ticker q are computed as

[7] All three exchanges have opening times between 08:00 and 16:30 (GMT). The raw dataset contains only reported trades, so no zero-volume observations are included. This stands in contracts to other datasets used in the literature, where market orders may contain zero-volume observations (pre-reporting).

$$VolSpr_q = \frac{\sum_{i=1}^{n} Vol_{qi} Spr_{qi}}{\sum_{i=1}^{n} Vol_{qi}} \tag{1}$$

$$PVolSpr_q = \frac{\sum_{i=1}^{n} P_{qi} Vol_{qi} Spr_{qi}}{\sum_{i=1}^{n} PVol_{qi}} \tag{2}$$

where Spr_{qi} is the raw (un-weighted) spread recorded during the 5-minute interval i, given as the simple difference between bid and ask quotes. The terms Vol_{qi} and P_{qi} denote the volume and price, respectively, of the sub-ticker during the 5-minute interval i. Sub-ticker subscripts are omitted for notational convenience. On each day, we compute both measures of spread separately for each sub-ticker, and then use the average across sub-tickers as the spread of ticker q on that day.

In addition to spread, we use the quoted depth (*Depth*) as a reciprocal measure of liquidity (see for instance Harris, 1990), measured as the quoted volume averaged across the 5-minute intervals. Furthermore, we compute logarithmic intraday returns r_i per interval i, based on midquote prices at a sub-ticker level, dropping outlying returns that are at least 3 standard deviations from the mean per ticker (99% of the computed returns are maintained post filtering).

One of our objectives is to understand if idiosyncratic characteristics have an impact on the extent to which the liquidity of a particular option is driven by the common liquidity factor. To this end, we examine a wide set of stock-specific and option-specific characteristics. More specifically, we follow Andersen et al. (2001) to compute the daily option price realized volatility (*OPRV*) as the sum of absolute intraday returns per ticker[8]

$$OPRV_q = \sum_{i=1}^{n} |r_{qi}| \tag{3}$$

where r_{qi} is the return of ticker q during the interval i. Furthermore, we use a range estimator as a measure of the underlying market volatility as follows (see Parkinson, 1980 and Petrella, 2006).

[8] Measuring volatility using absolute returns has the advantage of mitigating the impact of extreme (tail) observations, compared to using squared returns (see, for instance, Davidian and Carroll, 1987). For robustness, we have also used the average of squared intraday returns as an alternative proxy for volatility. The results are almost identical to those obtained when absolute intraday returns are used.

$$Vol_t = 100 \times \frac{P_t^{max} - P_t^{min}}{\frac{P_t^{max} + P_t^{min}}{2}} \tag{4}$$

where P_t^{max} and P_t^{min} refer to the maximum and minimum daily underlying price of each ticker on trading day t, respectively. The remaining idiosyncratic variables that we consider comprise the number of option transactions per interval (Fr), the market value of the underlying stock (MV), and the underlying percentage bid-ask spread ($PBAS$).

3.2 Extracting a Commonality in Liquidity Factor

The levels of individual liquidity of options that trade in the same exchange are very likely to exhibit a significant degree of collinearity, given that they are affected by factors that are common to multiple assets. In order to investigate the cross-sectional commonality in liquidity for tickers trading in Amsterdam, London and Paris, we employ the well-established methodology of Principal Component Analysis (PCA). PCA is a variable reduction procedure that, in this context, is applied to derive a smaller set of variables that will account for most of the variations in spreads per ticker. Importantly, the set of factors extracted by the PCA can be viewed as the most important uncorrelated sources of liquidity variation across tickers.

For each ticker, and separately for calls and puts, we select the ATM, ST contracts at 5-minute intervals for the whole sample period. There are 101 intraday intervals i for each day t. Because several sub-tickers may fall within the ATM, ST category per ticker, we estimate the average liquidity measure for each ticker and interval i. As the number of contracts j is smaller than the number of intervals i, PCA can be performed for each trading day. Finally, we apply PCA separately for calls and puts in each exchange, and we extract the first three principal components on each day. This approach results in six triplets of common factors per day, across two types of options (calls vs puts) and three exchanges.

In order to accommodate missing data, we apply two criteria. First, for each day, we only use tickers that report quotes for 80% of the number of intervals. Second, we interpolate missing values by using the most recent liquidity estimate i.e. if spread is missing for the interval i, then we use the most recent interval to replace the missing value. If the first interval of the day is missing, we use the first available non-missing value of the day. This allows us to retain the maximum number of tickers per day and also to use a n x j matrix where the number of intervals per day n is greater than the number of tickers i. All ticker measures are standardized by the daily mean and daily standard deviation per ticker in order to avoid overweighting because of scale differences (see Korajczyk and Sadka, 2008).[9]

As the PCA code is iterated on each trading day, the proportion of assets included in the calculation of the common factors may vary. We make sure that our measure of liquidity commonality is robust to missing observations that result in a varying number of available assets per day as follows. First, we perform all the subsequent empirical analysis with the entire dataset and for the sub-sample of days when more than 30% of the total number of assets is included in the calculation of the common factors. The empirical results are quantitatively similar in both cases. We also calculate the ratio of the number of assets included in the calculation of daily common factors over the total number of assets quoted on a single day. The correlation ranges from -11% to 14%, hence we believe that the results are invariant to the total number of assets included per day (results available upon request). Overall, we believe that the commonality in liquidity measure mostly captures those assets that are the most frequently traded, as generally assets that report more trades also tend to be more active in quotes.

3.3 Research Design

Once we have constructed the liquidity commonality factor as the main principal component of the previous analysis, we examine this factor's time-series properties. We are also interested in the extent to which the main factor can explain the cross-sectional variation in liquidity, separately for each exchange. A second question that we ask is which firms display significant and consistent loadings on the main factor. Since we extract the main principal component independently for each trading day, we are able to determine which firms contribute the most to the first principal factor. In other words, we identify which tickers in essence contribute the most to systematic liquidity. Given that we are using standardized balanced data per day, this process is independent of any price level effects or the trading volume of any firm.

Another question of interest is the extent to which the daily commonality in liquidity is able to explain individual variations in liquidity (see Korajczyk and Sadka, 2008). We address this question through a two-step approach. First, we regress each sub-ticker's

[9] Because prices do not vary substantially during a trading day and since we extract the PCA factors at a daily frequency, we employ this method to the percentage quoted spread instead of the volume-weighted spread.

liquidity against the liquidity factors extracted from the PCA discussed above. We run these time-series regressions separately for up to three principal factors and we keep the proportion of variance explained by the principal factors, as given by the respective Adj-R^2 values. The second step involves estimating cross-sectional regressions of the price-volume-weighted spread against the previously obtained Adj-R^2 values. The cross-sectional Adj-R^2 from the second-stage regressions captures the ability of the principal components to explain the variation in liquidity at the sub-ticker level.

We investigate the determinants of systematic liquidity by considering market-wide factors that are related to the options and the underlying market. More specifically, we estimate the following time-series regression

$$\begin{aligned} Pro_t = \beta_0 + \beta_1 V_t + \beta_2 IV_t + \beta_3 SS_t + \beta_4 DoW_t + \beta_5 Y09_t + \beta_6 Y10_t \\ + \beta_7 Sentiment_t + \beta_8 R_t^{-/+} + \beta_9 PR_t^{-/+} + u_t \end{aligned} \tag{5}$$

where the dependent variable (*Pro*) is the proportion of variance explained by the common factor. The terms V and IV refer to index volume and index implied volatility, respectively. We use the AEX Index for Amsterdam, FTSE100 for London and CAC40 for Paris. All values refer to the nearest-the-money call and put contracts that are available on DataStream. SS is the short sale dummy that takes the value of one in the first month of the short selling restriction period.[10] The term DoW is a day-of-the-week dummy that takes the value of one if the trading day is Monday-Thursday and zero if it is Friday. The $Y09$ and $Y10$ dummy variables take the value of one if the year is 2009 and 2010, respectively, while *Sentiment* refers to the put-to-call ratio across all tickers per day. The term R^+ refers to the contemporaneous return rate and takes the value of one if it is positive and zero otherwise, while PR^+ refers to the past trading activity and takes the value of one if returns in the last three trading days are positive and zero otherwise. Similarly, R^- and PR^- refer to past and contemporaneous negative index returns and enter the specification when contemporaneous returns are negative. Further, we include year dummies and short sale dummies that are designed to capture the time-variation in liquidity commonality due to these factors. Statistical inference is based on Newey-West autocorrelation and heteroscedasticity consistent standard errors.

We expect commonality in liquidity to be positively related to trading volume as the latter reflects changes in inventory risk. The common liquidity factor is also expected to

[10] We only include the first month of the short selling restriction ban as this variable would otherwise overlap with the year dummy variable.

be positively related to options market-wide volatility. Positive option market returns are likely to induce more trading and increase systematic liquidity, thus we expect a positive sign for the coefficient of positive contemporaneous returns and a negative sign for negative ones. In univariate analysis, we find that the commonality in liquidity follows a U-shaped pattern over the trading week (results not reported for brevity). In particular, the proportion of variance explained by the main common factor is high on Mondays, levels off from Tuesday to Thursday and is at maximum levels on Fridays.[11] Regarding the sentiment variable, we anticipate a positive coefficient for calls and a negative coefficient for puts if liquidity commonality increases when investors become more bearish. Finally, positive (negative) past trading activity is related to momentum strategies that are hypothesized to have a positive (negative) effect on systematic liquidity (see also Chordia et al., 2001).

In addition, we investigate if the extent to which the common factor explains the liquidity variability of individual tickers depends on the ticker's idiosyncratic characteristics. To this end, we adopt again a two-step approach. The first step is similar to the one previously described, where price-volume-weighted spread for a given sub-ticker is regressed against the first factor from the PCA. The Adj-R^2 of this time-series regression reflects the proportion of the sub-ticker's liquidity variance that can be explained by the common factor. We perform one time-series regression per sub-ticker. The second step, then, involves estimating a regression of the previously obtained Adj-R^2 values against a set of firm-specific characteristics, namely Market Value (MV), mean underlying volatility (Vol), underlying percentage bid-ask spread ($PBAS$), the frequency of transactions (Fr), the option realized volatility (OPRV), and the options' trading volume ($OVol$).

Finally, we explore the possibility of potential spill-overs of liquidity commonality among option markets. In order to understand the linkages between the three options exchanges in terms of liquidity commonality, we employ a standard Vector Autoregression (VAR) framework which recognizes the potential endogeneity of all variables in the system and allows for the inclusion of lagged values (as opposed to simply computing pairwise correlations). The VAR model is given as

[11] We tested the above hypothesis with a delivery-day dummy. We have also tested for GDP, CPI and unemployment announcement effects. No delivery day or announcement effects were detected. This pattern could theoretically be associated with the maturity cycle of equity options as these contracts expire on the third Friday of the expiry month. However, given that in this sample we do not include contracts within the last week prior to expiry, such interpretations are highly unlikely.

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \varepsilon_t \quad (6)$$

where Y_t is a 6x1 vector of variables. More specifically, the variables in the VAR system refer to the proportion of liquidity variance explained by the common factor, measured separately for calls and puts in each of the three exchanges (resulting in a total of six time-series).

4. Empirical Results

4.1 Time-Series of Individual Liquidity

Before discussing the relative importance of the common liquidity factor for options liquidity, it is important to get a better understanding of our time-series of interest. To this end, Table 1 presents some descriptive statistics of the two liquidity measures, separately for calls and puts, as well as for each market. The average spread varies significantly across markets, from a level of 0.12 cents for Amsterdam and 0.24 cents for Paris, to between 1.06 and 42.91 pence for London.[12] Calls are found to have significantly different spreads compared to puts for all three markets, as evidenced by both the t-test and the non-parametric Wilcoxon test.

insert Table 1 here

Figure 1 plots the price-volume-weighted quoted spread and depth across the three exchanges, separately for calls and puts.[13] As can be easily seen, option liquidity exhibited significant variability over the 34-month sample period, with a set of spikes in liquidity being associated with important systematic events. For instance, liquidity dropped substantially across all three markets during early September 2008, coinciding with the rescue by the US government of Fannie Mae and Freddie Mac. For Amsterdam, the biggest liquidity drop (highest spread, lowest depth) took place on October 10, 2008 when several European exchanges, as well as the Dow Jones and the Nikkei, lost a considerable part of their market value. For London and Paris, liquidity was at its lowest on October 23, 2008 after a consistently negative trend during that month.

[12] These numbers are not rounded, since spreads are estimated as the average of sub-tickers' spreads per contract per day.

[13] Each plot is constructed as the equally-weighted average of the daily average quoted spread per trading day and ticker. We standardize all measures, using their means and standard deviations, in order for the resulting liquidity series to be comparable across markets.

insert Figure 1 here

In addition to observing spikes on the Figure, periods of significant illiquidity can also be identified when spread plots above depth. This is evident during the period from September 2008 to March 2009, when the short-sale ban on financial stocks was imposed across all three markets (starting on September, 19 in London, and September, 23 in Amsterdam and Paris). Finally, we also plot on Figure 1 the ratio of put-to-call traded volume. This measure is a well-established proxy for investor sentiment in the sense that higher values of the ratio are the result of more puts being bought relative to calls, meaning that investors are more likely to expect asset prices to fall. Trading in puts generally increases throughout the period from September 2008 to February 2009, and it reaches its peak in Amsterdam in the midst of the financial crisis (October 13, 2008). The put/call volume ratio correlates strongly with the liquidity measures for Amsterdam (correlation coefficients of 0.63 and -0.27 regarding spread and depth, respectively), which is hardly surprising given the significant presence in the market of retail investors who are generally more prone to trading on sentiment. The respective correlations are quite weaker for London (0.17 and 0.01 regarding spread and depth, respectively) and Paris (0.19 and -0.11 for spread and depth, respectively), where the activity of retail investors is fairly limited.

4.2 Liquidity Commonality and Variation in Individual Liquidity

As has been previously discussed, we extract the first three components from the PCA on each trading day, separately for calls and puts and for the three options exchanges in our sample. Table 2 reports the respective PCA results using the daily time-series of spread and depth. More specifically, Panel A refers to using Spread as a measure of liquidity and tabulates the eigenvalue, the proportion of variance explained by each of the three factors, and the cumulative proportion of variance explained by up to three factors. Panel B reports the same figures when liquidity is measured by Depth. Panel C reports the first three canonical correlations between spread and depth liquidity. As can be seen from the Table, the common factors can explain a large proportion of the variance of liquidity at the daily level for both calls and puts across all three exchanges. For instance, the first principal component can explain 36% of the variation of spread in the panel of daily options liquidity for Amsterdam calls, while the respective figure reaches 55% when the first three principal components are used. The explanatory power of liquidity commonality is comparably high for the Paris and Amsterdam, with the proportion of spread liquidity variance explained by the first three factors exceeding 50% in all cases. The PCA results are even stronger in the case of depth, with the first three factors accounting for over 60% of the variance of depth liquidity for both calls and puts in all three exchanges.

insert Table 2 here

When we replicate the PCA separately for each trading day (directly using intra-daily data for spread and depth as opposed to the daily time-series discussed in sub-section 3.2), we find that the proportion of liquidity variance that can be explained by systematic liquidity is again considerably high. The time-series of the common factor's explanatory power over liquidity variance can be seen in Figure 2. The vertical axis of Figure 2 uses the proportion of variance explained by the principal factor instead of the eigenvalue of that factor, as the latter does not take into account the number of assets included in the calculation of this factor. For Amsterdam and on average, 15% of the daily total variance of liquidity among tickers is explained by a common factor, although it is also clear that commonality increases when liquidity deteriorates. This is clearly consistent with events during the financial crisis. Compared to the time series of volume-weighted spread, the commonality of liquidity is relatively constant outside those liquidity spikes and rarely falls below the 10% level. For London, the average cross-sectional variance explained per day is 27% and, compared to the results for Amsterdam, commonality in liquidity is more variable and tends to exhibit more spikes. For both markets, systematic liquidity generally increased during the financial crisis period. For Paris, the proportion of cross-sectional variance explained is 27% and, in general, the time series is very similar to the distribution of the principal factor for London.

insert Figure 2 here

In addition to the ability of the common factor to explain the liquidity of individual options at the level of the cross-section, we examine the proportion of liquidity variance at the level of the individual ticker that can be explained by the common factor. To this end, Table 5 reports the mean Adj-R^2 from estimating time-series regressions of the price-volume-weighted spread per ticker against the first principal factor. In general, liquidity commonality is found to explain about 11% of the variability at a sub-ticker level. There is variability in the percentage of variance explained by the main principal factor. For Amsterdam, the mean Adj-R^2 is approximately 14% and a similar figure is found for London. For Paris, the average Adj-R^2 is 6%. The percentage of variation explained by the commonality factor increases as the number of factors included in the regression increases. When all three main factors are included in the regressions, systematic liquidity explains on average 15% of the variation at a ticker level. This figure ranges from 8% for Paris puts to 17% for Amsterdam puts. These results demonstrate less commonality in liquidity than observed for US equities (see Korajczyk and Sadka, 2008). However, it is by definition much more demanding to detect commonality in daily liquidity than at the monthly frequency used in Korajczyk and Sadka (2008).

insert Table 3 here

Next, we turn to identifying which firms tend to be more significantly and consistently associated with the common liquidity factor. Figure 3 presents those tickers that consistently appear with significant loadings in the first principal factor as a proportion of the total number of trading days. For example, MT for Amsterdam calls is a significant contributor to systematic liquidity for approximate 352 days in our sample (50% of 703, the total number of trading days).[14] Clearly, across markets and contract types, there are firms that contribute much more than others to liquidity commonality. For Amsterdam there are seven tickers that appear on more than 40% of the trading days in the first principal factor and, in general, the same firms have significant loadings for puts. For London calls, two tickers have significant loadings for more than 558 days, or more than 80%. Finally, for Paris, there are 14 tickers that exhibit a proportion of 50% or greater towards their overall contribution to the first principal factor.

4.3 Liquidity Commonality and Market-Wide Factors

After establishing that systematic liquidity can explain a considerably large, albeit varying, proportion of individual options' liquidity, we shift our focus on examining if this explanatory power of the common factor depends on market-wide variables. Table 4 reports the results from estimating the time-series regression in (5), separately for

[14] We only present tickers with a contribution greater than 5%.

calls and puts and for each of the three exchanges. We also estimate the regression separately for positive and negative trading activity (contemporaneous and past).

insert Table 4 here

As hypothesized, market volume has a positive impact on systematic liquidity, although the result is only significant for Amsterdam. The market-wide implied volatility is clearly the strongest and most consistent determinant of systematic liquidity. The short sale dummy is negative and significant for 5 out of 6 regressions. One explanation for this is that the short sale restriction affected financial stocks only. If this is the case, then the plot observed in Figure 2 reflects news announcements rather than the short sale ban.

The drop in liquidity commonality is confirmed for Fridays and the result is highly significant for London and Paris. Also liquidity commonality drops significantly in 2009 for all three markets. A similar pattern is observed for 2010. Finally, there is a consistent response to market performance. Sentiment is only significant for Amsterdam calls, a finding that may reflect the fact that retail activity in Amsterdam is much more pronounced than in London or Paris. Commonality in liquidity for calls increases in an up market whereas puts remain unchanged. Also, commonality in liquidity decreases in a down market for calls. Such an asymmetric response of commonality in liquidity to return variation is also observed by Cao and Wei (2010) for the US options markets.

4.4 Liquidity Commonality and Idiosyncratic Characteristics

Our previously reported results highlighted the fact that different tickers exhibit different sensitivities to the common liquidity factor. We further explore this finding by investigating the determinants of the extent to which the liquidity of a particular asset is affected by liquidity commonality. Table 5 reports the results from estimating a cross-sectional regression of the proportion of liquidity variance explained by the common factor against a set of idiosyncratic characteristics.

insert Table 5 here

The results support the hypothesis that the impact of the common factor on individual liquidity depends on firm-specific characteristics. More specifically, we find that the number of options transactions per time interval (Fr) is positively and significantly related to the impact of the common liquidity factor. In contrast, the trading volume of options and the options' realized volatility are significantly negatively related to the explanatory power of the common factor. These findings hold for both calls and puts, and they seem to indicate that individual liquidity is more responsive to the common factor when trading in assets is characterized by a larger number of relatively low-volume transactions at low levels of volatility. At the other end of the spectrum, assets with higher volatility that are traded in larger blocks and more infrequently seem to be less exposed to the common liquidity factor.

Furthermore, the percentage bid-ask spread (*PBAS*) is positively related with the proportion of variance explained by the common factor only in the case of puts, while the firm's market value (*MV*) is positively related to the impact of the common factor only for calls. Finally, the coefficient of the volatility of the underlying stock (*Vol*) is insignificant for calls and puts. Overall, the previously documented differences in the explanatory power of liquidity commonality over individual liquidity among assets seem to be driven, to a significant extent, by some of these assets' idiosyncratic characteristics.

4.5 Liquidity Commonality Spill-Overs

The final analysis relates to whether liquidity commonality effects spill-over from one exchange to another. Estimating the VAR system described in sub-section 3.3 provides some, albeit not extensive, support for the hypothesis of the explanatory power of the common liquidity factor being interrelated among the three exchanges. In particular, Table 6 reports the results from estimating the VAR system in equation (6).

insert Table 5 here

Out of the three options exchanges, Amsterdam appears to be the one for which the explanatory power of the common liquidity factor is significantly related to that of the other two exchanges. More specifically, the effect of the common factor extracted from Amsterdam options (calls and puts) is significantly positively related to the respective series from Paris calls and negatively related to that of Paris puts at the first lag. Amsterdam calls are, in addition, significantly positively related to London calls at the first lag, although a similar relationship is not found in the case of puts. In the case of London, calls are significantly negatively related to Paris puts, and puts are significantly positively related to Amsterdam puts. Finally, the explanatory power of the common factor for Paris puts is significantly related to that of Amsterdam and London puts, while

Paris calls are only significantly related to London calls. Overall, some spill-over effects seem to be present, with the effects of the common liquidity factor being, to a limited extent, interconnected among the three options exchanges of NYSE LIFFE.

5. Conclusions

Despite the substantial literature on the liquidity of equity markets, the issue of options' liquidity has only recently begun to attract attention. This paper contributes to the literature on the liquidity of individual equity options, from the specific viewpoint of liquidity commonality. In particular, we examine the relatively underexplored European market of NYSE LIFFE using an extensive high-frequency dataset of options trading in Amsterdam, London and Paris.

Our empirical findings highlight the importance of a common liquidity factor for the liquidity of individual equity options. In particular, we find that systematic liquidity can explain a large part of the variation in liquidity across individual options, ranging from 15% for Amsterdam to 27% for London and Paris. Therefore, our index of commonality in liquidity serves as an important driver of liquidity for individual equity options. The explanatory power the common liquidity factor depends on market-wide factors, especially in terms of being significantly higher during periods of greater market uncertainty, as reflected in higher index implied volatility. Moreover, individual tickers are found to be more responsive to the common liquidity factor when they are characterized by more frequent, low volume and low volatility trading.

Documenting the significant presence of a common liquidity factor in options, and understanding its relationship with market-wide and idiosyncratic variables has important implications in several contexts. For instance, individual asset returns could command a risk premium for exposure to systematic liquidity risk, in addition to the premium related with the asset's particular level of individual liquidity. More importantly, understanding the dynamics of the common liquidity factor could provide a useful framework for anticipating, and ultimately preventing, cases where a breakdown in liquidity can escalate to a full-blown crisis, even in the absence of other significant events.

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Table 1
Descriptive statistics

	Amsterdam		London		Paris	
	Call	Put	Call	Put	Call	Put
No. of days	707		709		712	
No. of tickers	65(72)	65(72)	99(106)	99(106)	59(70)	59(70)
Spread						
Mean	0.12	0.11	6.31	6.29	0.25	0.25
Min	0.03	0.03	1.06	1.04	0.04	0.04
Max	0.36	0.38	42.91	41.97	1.08	1.11
STD	0.06	0.06	5.95	5.85	0.17	0.17
Depth						
Mean	385.38	395.77	22.12	22.04	60.94	60.82
Min	20.20	19.68	3.06	3.07	16.88	17.39
Max	2039.45	2096.40	227.67	228.12	202.74	216.44
STD	518.74	531.98	27.50	27.58	42.43	42.94

Notes: Number of tickers refers to the total number of firm-options trading at the exchanges and includes delisted options, given as the total number of contracts separately for calls and puts. In parentheses, the number of tickers in the original (raw) dataset. *Spread* refers to the price-volume weighted quoted spread. *Depth* refers to the quoted volume. Both *Spread* and *Depth* per ticker are computed as the means of intra-daily 5-minutes values, also averaged across sub-tickers. For Amsterdam and Paris, prices are quoted in Euros per contract whereas for London prices are quoted in pence per contract, hence the discrepancy in the results. Depth is calculated from the average of bids plus asks per five minute interval, aggregated to daily estimates. The t-test and Wilcoxon test for the equality of means between calls and puts for Spread and Depth are uniformly rejected.

Table 2
PCA results for the commonality in liquidity and canonical correlations

Panel A

		Amsterdam						London						Paris					
		Call			Put			Call			Put			Call			Put		
Spread		Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
	Eigenvalue	13.152	4.258	2.772	13.843	4.316	2.649	20.675	7.208	3.921	21.741	8.105	3.976	10.428	4.288	3.390	11.610	4.496	3.788
	Proportion	0.356	0.115	0.075	0.374	0.117	0.072	0.345	0.120	0.065	0.362	0.135	0.066	0.290	0.119	0.094	0.323	0.125	0.105
	Cumulative	0.356	0.471	0.546	0.374	0.491	0.562	0.345	0.465	0.530	0.362	0.497	0.564	0.290	0.409	0.503	0.323	0.447	0.553

Panel B

		Amsterdam						London						Paris					
		Call			Put			Call			Put			Call			Put		
Depth		Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
	Eigenvalue	9.985	9.432	3.147	9.572	8.700	3.448	22.786	9.634	4.587	23.058	9.420	4.622	10.889	6.213	5.066	11.051	6.216	4.847
	Proportion	0.270	0.255	0.085	0.259	0.235	0.093	0.380	0.161	0.077	0.384	0.157	0.077	0.303	0.173	0.141	0.307	0.173	0.135
	Cumulative	0.270	0.525	0.610	0.259	0.494	0.587	0.380	0.540	0.617	0.384	0.541	0.618	0.303	0.475	0.616	0.307	0.480	0.614

Panel C

		Amsterdam		London		Paris	
	Root no.	Call	Put	Call	Put	Call	Put
CanCorr	1	0.954	0.948	0.974	0.971	0.952	0.961
	2	0.908	0.897	0.907	0.938	0.939	0.941
	3	0.796	0.843	0.887	0.914	0.845	0.847
	Wilks' Lambda	4.9E-06	3.0E-06	1.7E-10	7.3E-11	2.4E-06	1.9E-06
	F-test	6.500	6.825	4.392	4.606	8.445	8.636
	P-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Panel A and Panel B show the proportion of spread and depth liquidity explained by the first three common factors, respectively, as obtained from estimating a principal Component Analysis (PCA). *Spread* refers to the price-volume weighted quoted spread. *Depth* refers to the quoted volume. Both *Spread* and *Depth* per ticker are computed as the means of intra-daily 5-minutes values, also averaged across sub-tickers. *Proportion* refers to the proportion of variance explained by each factor. *Cumulative* refers to the cumulative proportion of variance explained by adding extra factors. Panel C shows the first three canonical correlations between spread and depth liquidity. The results are tabulated separately for the Amsterdam, London and Paris exchanges, and also separately for calls and puts.

Table 3
Proportion of individual liquidity explained by the common factors

No. of Factors	Amsterdam		London		Paris	
	Call	Put	Call	Put	Call	Put
1	0.13	0.14	0.15	0.14	0.07	0.05
2	0.15	0.15	0.16	0.15	0.09	0.07
3	0.19	0.17	0.18	0.16	0.11	0.08

Notes: This table shows the proportion of liquidity explained by the first three common factors, estimated from time-series regressions. The dependent variable is the price-volume weighted spread per day, and the independent variables are the common liquidity factors obtained from the PCA. Each cell represents the average Adj-R2 for up to three main principal factors. The results are tabulated separately for the Amsterdam, London and Paris exchanges, and also separately for calls and puts.

Table 4

Regression results for the proportion of variance explained by the principal common factor against market-wide characteristics

	Amsterdam		London		Paris		Amsterdam		London		Paris	
	Call	Put	Call	Put	Call	Put	Call	Put	Call	Put	Call	Put
V	0.027	0.023	0.008	0.003	-0.003	0.003	0.026	0.022	0.008	0.004	-0.002	0.004
	(3.51)***	(3.28)***	(1.00)	(0.37)	(-0.41)	(0.54)	(3.46)***	(3.36)***	(1.05)	(0.41)	(-0.33)	(0.56)
IV	0.331	0.317	0.512	0.527	0.741	0.662	0.317	0.304	0.497	0.511	0.73	0.644
	(6.23)***	(6.23)***	(7.54)***	(8.01)***	(9.91)***	(8.82)***	(6.06)***	(6.15)***	(7.28)***	(7.66)***	(9.69)***	(8.44)***
SS	-0.040	-0.041	0.009	-0.011	0.009	0.013	-0.037	-0.039	0.014	-0.005	0.011	0.015
	(-3.63)***	(-4.07)***	(0.4)	(-0.45)	(0.48)	(0.63)	(-3.41)***	(-3.89)***	(0.6)	(-0.20)	(0.56)	(0.73)
DoW	-0.005	-0.010	-0.032	-0.034	-0.026	-0.023	-0.004	-0.010	-0.032	-0.033	-0.026	-0.023
	(-0.80)	(-1.84)*	(-3.96)***	(-3.99)***	(-3.23)***	(-2.63)***	(-0.77)	(-1.82)*	(-3.94)***	(-3.95)***	(-3.20)***	(-2.68)***
Y09	-0.018	-0.023	-0.066	-0.056	-0.016	-0.004	-0.018	-0.023	-0.063	-0.052	-0.015	-0.002
	(-3.24)***	(-4.44)***	(-5.62)***	(-4.91)***	(-1.60)	(-0.45)	(-3.27)***	(-4.44)***	(-5.44)***	(-4.53)***	(-1.45)	(-0.29)
Y10	0.004	-0.007	-0.049	-0.040	0.058	0.070	0.003	-0.008	-0.049	-0.039	0.059	0.070
	(0.46)	(-1.04)	(-4.54)***	(-3.66)***	(6.36)***	(8.25)***	(0.42)	(-1.14)	(-4.41)***	(-3.50)***	(6.47)***	(8.29)***
Sentiment	0.023	0.019	< 0.001	-0.004	0.004	0.005	0.020	0.017	< 0.001	-0.004	0.004	0.005
	(2.06)**	(1.29)	(0.18)	(-1.55)	(0.97)	(1.13)	(1.92)*	(1.2)	(0.12)	(-1.61)	(0.97)	(1.15)
R+	0.013	0.003	0.024	< -0.001	0.021	<- 0.001	.	.	.	.	.	.
	(3.01)***	(0.62)	(3.45)***	(-1.40)	(3.11)***	(-0.06)	.	.	.	.	.	.
PR+	0.009	0.009	0.015	0.025	0.013	0.012	.	.	.	.	.	.
	(1.59)	(1.53)	(1.48)	(2.03)**	(1.27)	(1.1)	.	.	.	.	.	.
R-	.	.	.	.	.	.	-0.012	-0.002	-0.023	0.009	-0.021	0.001
	.	.	.	.	.	.	(-2.78)***	(-0.43)	(-3.33)***	(1.31)	(-3.07)***	(0.18)
PR-	.	.	.	.	.	.	0.014	0.009	0.008	-0.008	0.004	0.020
	.	.	.	.	.	.	(1.25)	(0.88)	(0.53)	(-0.62)	(0.32)	(1.77)*
Con	-0.220	-0.162	0.116	0.180	0.077	0.039	-0.189	-0.151	0.139	0.173	0.096	0.041
	(-2.62)***	(-2.13)**	(1.45)	(1.87)*	(1.28)	(0.64)	(-2.40)**	(-2.13)**	(1.72)*	(1.81)*	(1.58)	(0.69)
R^2	0.29	0.32	0.37	0.34	0.41	0.39	0.29	0.32	0.36	0.33	0.41	0.39
Adj-R^2	0.28	0.31	0.36	0.33	0.40	0.38	0.28	0.31	0.36	0.33	0.40	0.38

Notes: This table shows the regression results for the proportion of variance explained by the principal common factor regressed against market-wide factors. *V* and *IV* refer to index volume and index implied volatility respectively. For Amsterdam, we use the AEX Index, FTSE100 for London and CAC40 for Paris. All values refer to the continuous nearest-the-market call and put contracts that are available on DataStream. R^+ refers to the current return rate and takes the value of one if it is positive and zero otherwise. PR^+ refers to the past trading activity and takes the value of one if returns in the last three trading days are positive and zero otherwise. Similarly, R^- and PR^- refer to past and present negative index returns. *SS* is the short sale dummy that takes the value of one in the first month of the short shelling restriction period. *DoW* is a day of the week dummy that takes the value of one if the trading day is Monday-Thursday and zero if it is Friday. The *Y*09 and *Y*10 dummy variables take the value of one if year is 2009 and 2010 respectively. *Sentiment* refers to the put-to-call ratio. T-statistics in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Table 5
Regression results for commonality in liquidity against firm-specific characteristics

	Call	Put
Constant	0.204***	0.214***
	(0.030)	(0.034)
MV	9.350E-07**	3.230E-07
	(0.000)	(4.860E-07)
Vol	-0.005	-0.006
	(0.006)	(0.007)
PBAS	0.065	0.155**
	(0.069)	(0.078)
Fr	0.002***	0.004***
	(0.001)	(0.001)
OPRV	-0.022**	-0.044**
	(0.011)	(0.014)
OVol	-4.630E-05**	-6.540E-05***
	(0.000)	(2.940E-05)
Adj-R^2	0.081	0.115

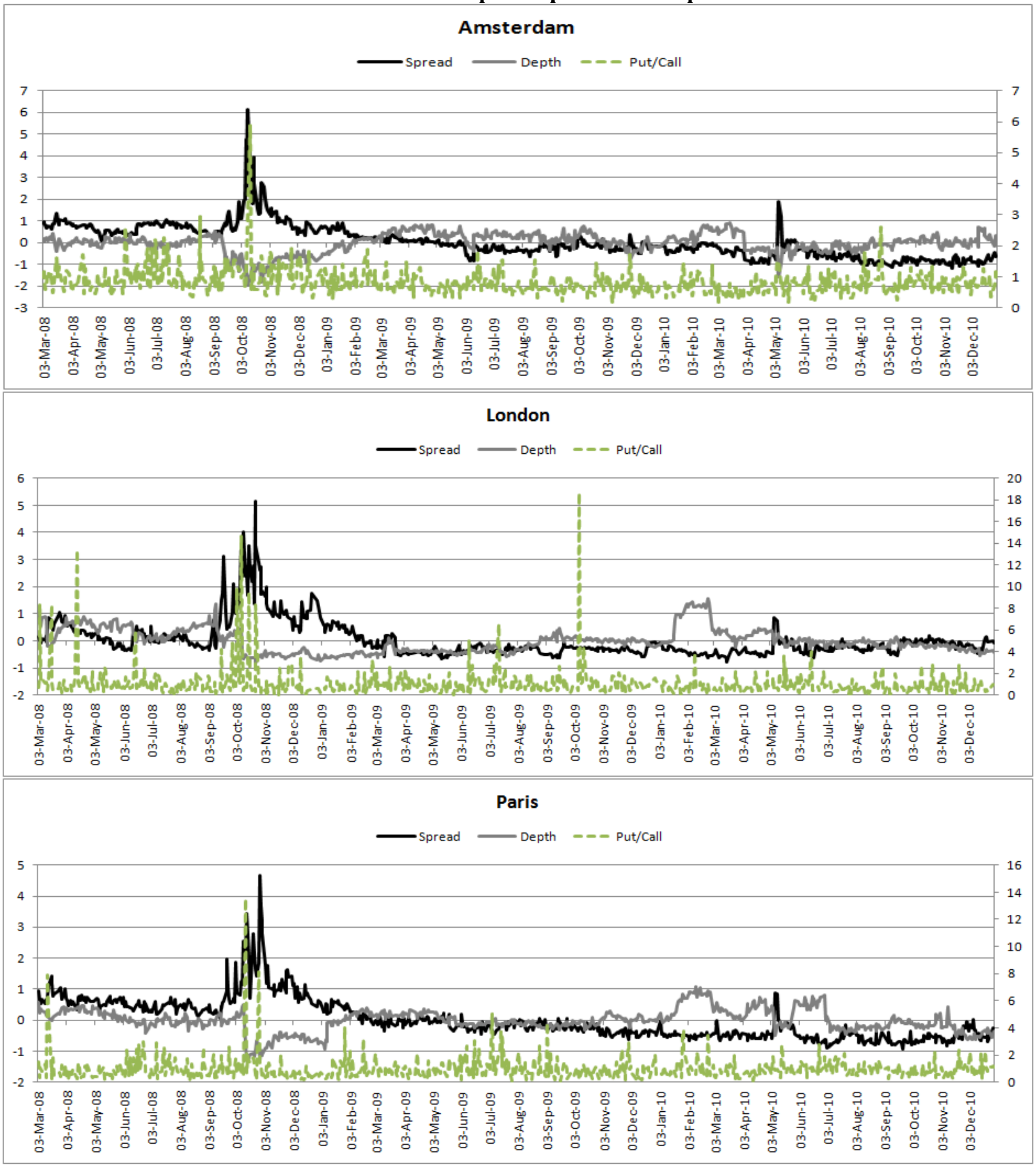
Notes: This table shows the results of the cross sectional regression of the proportion of variability explained by the first common factor for each asset against firm characteristics. The dependent variable refers to the Adjusted R^2 for each asset which is obtained by regressing the price-volume weighted spread against the first factor. *MV* refers to the mean market value per asset. *Vol* refers the mean underlying market volatility, *PBAS* refers to the mean underlying proportional bid-ask spread per asset, estimated from daily closing prices. *Fr* refers to the mean of transaction frequency and *OPRV* refers to mean option realized volatility per asset. *OVol* is the options trading volume per asset. Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Table 6
VAR: liquidity commonality by market

	Amsterdam		London		Paris	
	Call	Put	Call	Put	Call	Put
Constant	0.071***	0.072***	0.075***	0.105***	0.048***	0.063***
	(0.014)	(0.012)	(0.019)	(0.019)	(0.017)	(0.017)
Amsterdam call $_{t-1}$	-0.079	0.067	-0.104	-0.002	-0.166	-0.095
	(0.092)	(0.083)	(0.130)	(0.126)	(0.115)	(0.117)
Amsterdam call $_{t-2}$	0.057	0.050	0.163	-0.034	0.065	-0.158
	(0.092)	(0.084)	(0.131)	(0.128)	(0.116)	(0.118)
Amsterdam put $_{t-1}$	0.156	-0.019	0.164	0.155	0.125	0.138
	(0.103)	(0.094)	(0.147)	(0.143)	(0.130)	(0.132)
Amsterdam put $_{t-2}$	0.141	0.149*	0.117	0.214*	0.103	0.241**
	(0.091)	(0.082)	(0.129)	(0.126)	(0.115)	(0.116)
London call $_{t-1}$	0.148***	0.079	0.367***	0.298***	0.159**	0.066
	(0.056)	(0.051)	(0.080)	(0.077)	(0.070)	(0.071)
London call $_{t-2}$	-0.049	-0.001	-0.065	-0.013	-0.092	-0.067
	(0.054)	(0.049)	(0.077)	(0.075)	(0.068)	(0.069)
London put $_{t-1}$	0.008	0.015	0.237***	0.189**	0.031	0.005
	(0.056)	(0.050)	(0.079)	(0.077)	(0.070)	(0.071)
London put $_{t-2}$	-0.051	-0.068	0.081	0.097	-0.048	-0.110*
	(0.052)	(0.047)	(0.074)	(0.072)	(0.066)	(0.067)
Paris call $_{t-1}$	0.176**	0.216***	-0.047	-0.049	0.196**	0.220**
	(0.071)	(0.065)	(0.101)	(0.099)	(0.090)	(0.091)
Paris call $_{t-2}$	0.101	0.046	0.147	0.060	0.189**	0.148
	(0.068)	(0.062)	(0.097)	(0.095)	(0.086)	(0.087)
Paris put $_{t-1}$	-0.114*	-0.110*	0.036	0.016	0.246*	0.322*
	(0.066)	(0.060)	(0.094)	(0.091)	(0.083)	(0.084)
Paris put $_{t-2}$	-0.027	0.000	-0.175*	-0.142	0.107***	0.151***
	(0.066)	(0.060)	(0.093)	(0.091)	(0.083)	(0.084)
R^2	0.175	0.197	0.366	0.307	0.447	0.455

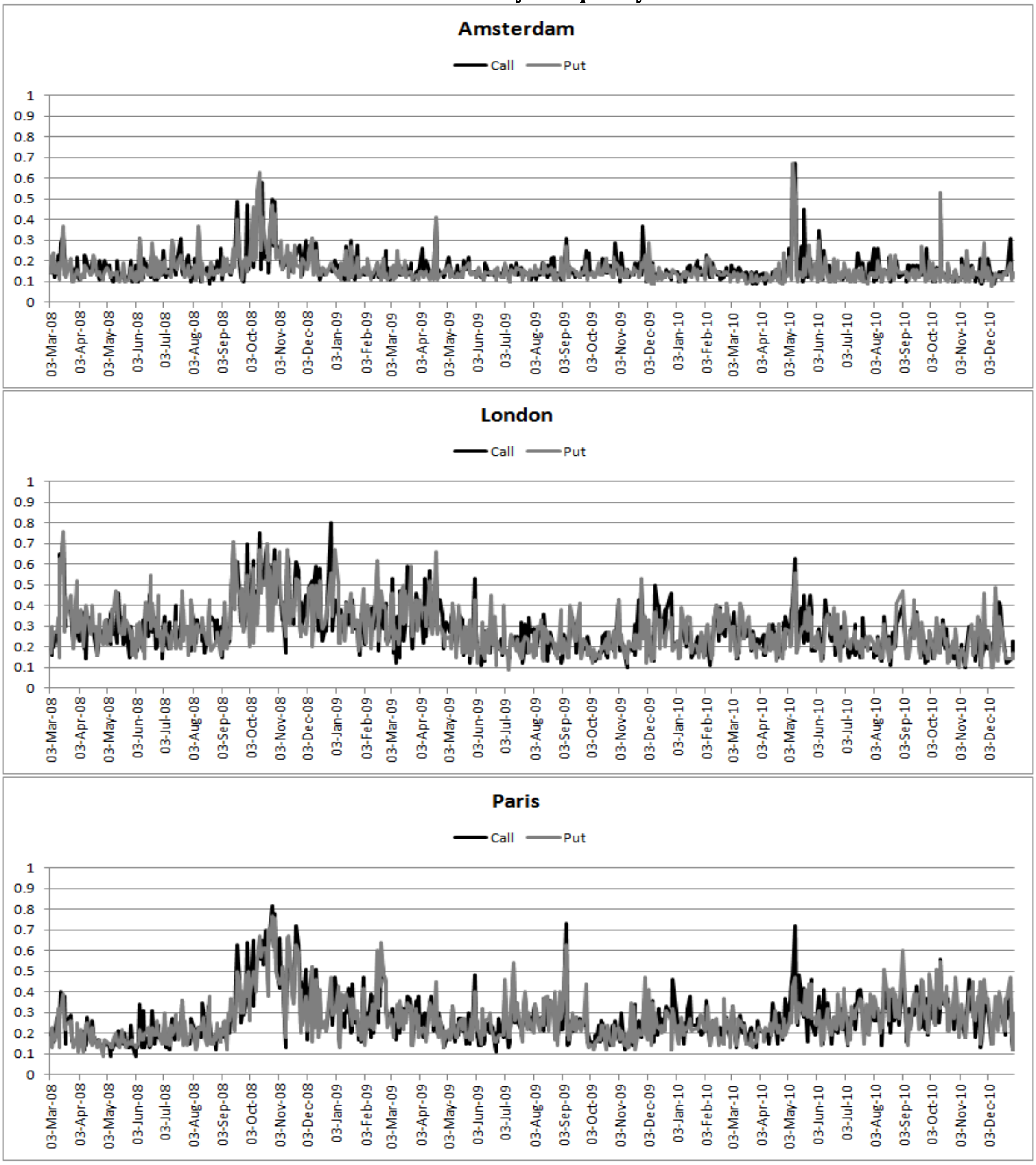
Notes: This table shows the VAR regression results for the proportion of variance explained by the principal common factor for each market. Standard errors in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Figure 1
Time series of option spread and depth



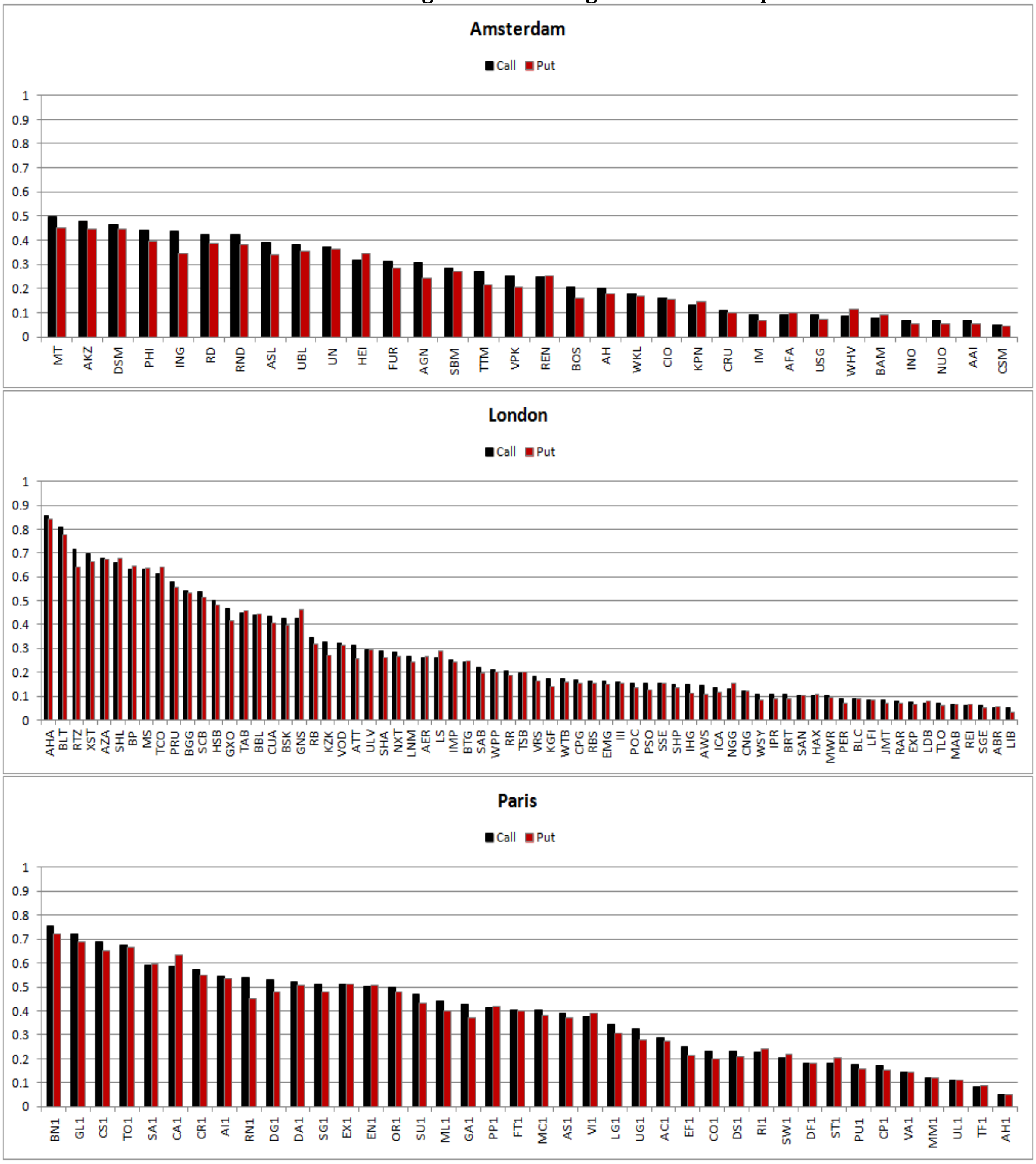
Notes: This figure shows the time series plots of individual equity options liquidity by exchange and contract type. Each plot is constructed as the equal-weighted average of the daily average quoted spread and depth per trading day and ticker. The put/call ratio refers to the ratio of put volume over call volume per trading day. All plots are standardized by the overall market mean and standard deviation to allow a visual comparison across markets.

Figure 2
Commonality in liquidity



Notes: This figure shows the time series of the proportion of liquidity explained by the main principal factors by exchange and contract type. The first principal component is extracted from the percentage bid-ask spread separately for each trading day with the procedure described in the main text.

Figure 3
Tickers that have a significant loading in the first component



Notes: This figure shows the tickers that have significant loading in the first component as a percentage of the total number of days in the sample. Only firms with over 5% are displayed. The first principal component is extracted from the percentage bid-ask spread separately for each trading day with the procedure described in the main text.