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Commonality in equity options liquidity:

Evidence from European Markets

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Abstract

This paper examines commonality in liquidity for individual equity options trading in European markets. We use high-frequency data to construct a novel index of liquidity commonality. The approach is able to explain a substantial proportion of the liquidity variation across individual options. The explanatory power of the common liquidity factor is more pronounced during periods of higher market-wide implied volatility. The common factor's impact on individual options' liquidity depends on options' idiosyncratic characteristics. There is some evidence of systematic liquidity spillover effects across these European exchanges.

JEL Classifications: G12; G19

Keywords: options; commonality; liquidity; bid-ask spread

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1. Introduction

Liquidity influences virtually every financial transaction and it has attracted increasing attention in the literature, especially after recent financial crises. One particularly important aspect of this issue relates to the role of common cross-asset variation in liquidity (see Karolyi, Lee and van Dijk, 2012 and Koch, Ruenzi and Starks, 2016). To the extent that liquidity across assets is driven by common factors, understanding the behaviour of liquidity's systematic component is fundamental in explaining, and ultimately anticipating, incidents of a general liquidity breakdown. The recent financial crises serve as clear examples of the dramatic impact that a break in systematic liquidity can have on global financial markets. Similar cases include the stock market crash of 1987 and the debt market crisis of 1998, which are typically viewed as systematic liquidity breakdowns (Hasbrouck and Seppi, 2001).

This paper examines systematic liquidity in European equity options markets. More specifically, we focus on the common factors that characterize the cross-asset variation in the liquidity of option contracts, and we study their determinants and the way in which they affect the liquidity of individual options. Cao and Wei (2010) extract a common liquidity component for the US markets but with daily data. In contrast, we use a large high-frequency dataset of equity options trading at Amsterdam, London and Paris, which currently form part of the InterContinental Exchange (ICE) group.

We employ Principal Component Analysis (PCA) to extract the common liquidity factor from individual equity options. The use of PCA with intraday equity options data is a novel approach and allows us to extract the common liquidity factor across option contracts (see Dunne, Moore and Papavassiliou, 2011 for an application to stocks). Our results highlight that common effects are significant drivers of options liquidity in European markets. 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 on average 11% of the liquidity variance at the firm level can be explained, with this proportion rising to 15% when we use the first three common factors.

Moreover, the explanatory power of commonality in liquidity for individual options depends 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 implied volatility of the market index. In particular, on days of greater uncertainty at the aggregate market level, as reflected by higher levels of index implied volatility, systematic liquidity makes a larger 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 investor activity is high.

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 most responsive to the common liquidity factor. The underlying asset's percentage bid-ask spread positively affects 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, we use a Vector Autoregression (VAR) framework to explore the possibility of linkages among the three options exchanges in terms of the systematic liquidity's explanatory power over individual options' liquidity. Our results highlight the presence of some interconnectedness among Amsterdam, London and Paris. However, these spillover effects are not particularly pronounced.

The remainder of the paper is organized as follows. Section 2 discusses the previous literature and this paper's contribution, while Section 3 presents the high-frequency options dataset used in the empirical analysis. Section 4 describes the methodology for extracting the liquidity commonality factor, variable construction and research design. Section 5 presents the empirical results, while Section 6 concludes.

2. Previous Literature and Contribution

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; Koch et al., 2016). 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 (Anderson et al., 2013; 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 equity options. 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; Kamara et al., 2008; Karolyi et al., 2012; 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, is 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, the European exchanges of the ICE group account for a large part of global exchange-based trading in options and, as such, their systematic liquidity component is likely to have a substantial impact on international investors .[2]

[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. (2016) also examine liquidity for options traded at NYSE LIFFE. However, they focus on the intraday determinants of liquidity for individual options, with only a brief mention

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 whether 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 these three European options exchanges.

Our third contribution relates to the use of high-frequency options data. Previous commonality studies have typically 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.

3. Data

The objective is to construct daily time-series of liquidity and volatility measures that incorporate the rich information available from intraday data (see 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 the ICE exchanges in Amsterdam,

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.

London and Paris from March 2008 to December 2010.[3] This 34-month intraday options dataset is long by the standards of the related literature using high-frequency derivatives data. 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). [4] 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.[5] 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.

In addition to selecting option contracts according to their moneyness and time-to-maturity, other filters are applied to the intraday dataset. First, we omit tickers for which we cannot find the respective underlying assets in DataStream. Second, we omit

[3] The options exchanges in Amsterdam, London and Paris were trading until recently under NYSE LIFFE. They are now part of the ICE group. A detailed discussion of their market structure appears in Verousis et al. (2016). Despite a significant effort to harmonize rules across the different European exchanges, several important differences remain. First, the options exchange in Amsterdam is at the cutting edge of high frequency trading (HFT), with Dutch firms 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.

[4] 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.

[5] End-of-day prices for the underlying stocks were obtained through DataStream.

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 mis-recordings by omitting observations with zero volumes, zero prices, negative or zero bid-ask spreads, and out-of-hours time-stamps.[6] Finally, we follow Wei and Zheng (2010) to omit observations with exceptionally large bid-ask spreads (exceeding 150% for ATM contracts). The majority of contracts are retained post filtering, with 90%, 93% and 84% of observations maintained for Amsterdam, London and Paris, respectively.

4 Methodology

4.1 Variable Construction

We compute liquidity measures of option sub-tickers based on 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 ask prices for each 5-minute interval and compute mid-quotes when both bids and asks are available for a particular interval, otherwise the mid-quote is treated as a missing observation. This approach allows us to construct observations for

[6] 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 contrasts with other datasets used in the literature, where market orders may contain zero-volume observations (pre-reporting).

the maximum number of intervals, after addressing potential biases of missing variables and stale pricing.

Similar 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

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

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

where Spr_{qi} is the raw (un-weighted) spread recorded during the 5-minute interval i, measured as the 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.

For each day, the spreads are computed for each sub-ticker separately by taking the weighted average (volume- or price-volume-weighted) of the quoted spreads that are observed across the n 5-minute intervals for that sub-ticker on that day. We then compute the volume-weighted and price-volume-weighted spread for a given ticker q as the average spread measure across its respective sub-tickers 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. We compute logarithmic intraday returns r_i per interval i, based on mid-quote 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 retained post filtering).

One of the objectives is to understand whether idiosyncratic characteristics influence 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[7]

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

where r_{qi} is the return of ticker q during the interval i. In the cases where two or more sub-tickers can be classified as ST-ATM for the same ticker on the same date, *OPRV* refers to the average volatility across these sub-tickers. Furthermore, we use a range estimator as a measure of the underlying market volatility as follows (see Parkinson, 1980 and Petrella, 2006).

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

where P_t^{max} and P_t^{min} refer to the maximum and minimum daily underlying stock price of each ticker on trading day t, respectively. All underlying data are obtained from DataStream. The remaining idiosyncratic variables 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*).

[7] 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 tests, we used the average of squared intraday returns as an alternative proxy for volatility. The results are almost identical to those obtained with absolute intraday returns.

4.2 Extracting the Commonality in Liquidity

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), which is an eigen decomposition of the sample covariance matrix. 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.[8]

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. As a result of this approach, on each day we obtain one time-series of liquidity per ticker across the 5-minute intervals. Finally, we apply PCA separately for calls and puts in each exchange, and we extract the first three principal components on

[8] Exploratory factor analysis represents an alternative approach for extracting the common liquidity factors. In fact, the PCA can be thought of as a more basic version of factor analysis. We opt for using PCA rather than factor analysis because the former approach can decompose variation in the system of options liquidity without the need to assume a particular underlying causal model. In contrast, factor analysis can result in more robust variance decomposition if some initial model formulations can be provided. Given that determining a particular form of the covariance matrix or formulating strong causal assumptions for the system of options liquidity is beyond the scope of this paper, we believe that the use of a mathematical "a-theoretical" transformation on the actual data through PCA represents a more appropriate approach for extracting the common liquidity factors in the context of this paper. For a more detailed discussion on the relative merits of factor analysis and PCA, please refer to Suhr (2009).

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 i 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 not sensitive to the total number of assets included per day (results available upon request).

[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.

4.3 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 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 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 $PVolSpr_q$ 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:

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

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, based on 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 *Y*09 and *Y*10 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 rate of return 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. 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 be positively related to options market-wide volatility. We expect that liquidity commonality will decrease in a bullish market, thus we expect a negative relationship between short sales and liquidity commonality. In univariate analysis, we find that the commonality in liquidity follows a U-shaped pattern across the trading week (results

[10] We only include the first month of the short selling restriction ban as this variable would otherwise overlap with the year dummy variable. Short-selling bans were introduced in Europe in September 2008, following the Lehman Brothers crisis.

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. If the latter is true, we expect a decrease in liquidity commonality in 2009 and 2010. 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. 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 whether 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 again adopt 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 volatility of underlying asset (Vlt), the underlying asset's percentage bid-ask spread ($PBAS$), the frequency of transactions (Fr), the option realized volatility (OPRV), and the options' trading volume ($OVlt$).

[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.

Finally, we explore the possibility of potential spill-overs of liquidity commonality across option exchanges. 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

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

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).

5. Empirical Results

5.1 Time-Series of Liquidity

Before discussing the relative importance of the common liquidity factor for options liquidity, it is important to offer an understanding of the time-series of relevant liquidity variables. To this end, Figure 1 plots the price-volume-weighted quoted spread and depth across the three exchanges, separately for calls and puts.[12] 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

[12] 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.

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 considerable market value. For London and Paris, liquidity was at its lowest on October 23, 2008 after a consistently negative trend during that month.

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 reaches its peak in Amsterdam in the midst of the financial crisis (October 13, 2008). The put/call volume ratio correlates 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 much weaker for London (0.17 and 0.01 for spread and depth, respectively) and Paris (0.19 and -0.11), where the activity of retail investors is fairly limited.[13]

[13] For a more detailed descriptive view of the underlying dataset, refer to Table 1 in Verousis et al. (2016).

5.2 Liquidity Commonality and Variation in Liquidity

As discussed in Section 4.2, 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 1 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. The last two figures can be considered as measures of the goodness-of-fit of the PCA, as they refer to the proportion of liquidity variance across tickers that can be attributed to the variation of the common factor. Panel B reports the equivalent results when liquidity is measured by depth. Panel C reports the first three canonical correlations between spread and depth liquidity. The common factors 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% for the first three principal components. 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 1 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 4.2), the proportion of liquidity variance that can be explained by systematic liquidity is again high. The time-series of the common factor's explanatory power over liquidity variance is presented 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. On average for Amsterdam, 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 recent financial crises. Compared to the time series of volume-weighted spread, the commonality of liquidity is relatively flat 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 peak periods of the sub-prime and European debt crises. 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. Table 2 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 19% for Amsterdam calls. These results demonstrate less commonality in liquidity than observed for US equities (see Korajczyk and Sadka, 2008). However, it is much more demanding to detect commonality in a daily liquidity series than at the monthly frequency used in Korajczyk and Sadka (2008).

insert Table 2 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 352 days (50% of the total number of 703 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.

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

insert Figure 3 here

5.3 Liquidity Commonality and Market-Wide Factors

After establishing that systematic liquidity can explain a large, albeit varying, proportion of individual options' liquidity, we shift our focus to examining whether this explanatory power depends on market-wide variables. Table 3 reports the results from estimating the time-series regression in equation (5), separately for 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 3 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 4 out of 12 regressions. One explanation for this is that the short sale restriction affected financial stocks only. The plot observed in Figure 2 probably reflects news announcements rather than the short sale ban.

The drop in liquidity commonality is confirmed for Fridays and this result is highly significant for London and Paris. Also liquidity commonality drops significantly in 2009 for all three markets. There is a more mixed pattern for 2010, as reflected in Figure 2. 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 and 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.

5.4 Liquidity Commonality and Idiosyncratic Characteristics

We have 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 4 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 (as discussed in Section 4.3).

insert Table 4 here

The results support a view that the impact of the common factor on individual option liquidity depends on firm-specific characteristics. Specifically, the number of transactions per time interval (Fr) is positively and significantly related to the impact of the common liquidity factor. 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 indicate that individual liquidity is more responsive to the common factor when trading in assets 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 have less relation 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 significantly positively related to the impact of the common factor only for calls. Finally, the coefficient of the volatility of the underlying stock (*Vlt*) 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 the assets' idiosyncratic characteristics.

5.5 Liquidity Commonality Spill-Overs

The final section of analysis relates to whether liquidity commonality spills over from one exchange to another. Table 5 reports the results from estimating the VAR system in equation (6).

insert Table 5 here

Estimating the VAR system described in Section 4.3 provides some support for the notion that the explanatory power of the common liquidity factor could be interrelated among the three exchanges. Among the three exchanges, Amsterdam is the case where the explanatory power of the common liquidity factor is most significantly related to that of the other two exchanges. That is, from a spillover perspective, we are interested in the interconnectedness of the home market with other markets, excluding the explanatory power of lagged home-market variables. 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 European options exchanges.

6. Conclusions

Despite the very substantial literature on equity market liquidity, the issue of options' liquidity has attracted sparse attention. This paper contributes to the literature on the liquidity of individual equity options, from the specific viewpoint of liquidity commonality. We examine the relatively underexplored European equity options market using an extensive high-frequency dataset of contracts 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 portion 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 captures an important driver of liquidity for individual equity options. The explanatory power of 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 options 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 to 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 financial market stress or crisis, even in the absence of other significant events.

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Table 1
PCA results for the commonality in liquidity and canonical correlations

Panel A

Spread	Amsterdam						London						Paris					
	Call			Put			Call			Put			Call			Put		
	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

Depth	Amsterdam						London						Paris					
	Call			Put			Call			Put			Call			Put		
	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

CanCorr	Amsterdam		London		Paris	
Root no.	Call	Put	Call	Put	Call	Put
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: Panels A and B present 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 presents 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 2
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 presents 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 3

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)
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 presents 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 present and past negative index returns. *SS* is a 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 the 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 4
Regression results for commonality in liquidity against firm-specific characteristics

	Call	Put
Constant	0.204***	0.214***
	(6.81)	(6.28)
Fr	0.002***	0.004***
	(3.00)	(3.43)
OVlt	-46.278**	-65.393***
	(-2.41)	(-2.23)
OPRV	-0.022**	-0.044**
	(-1.99)	(-3.21)
PBAS	0.065	0.155**
	(0.94)	(1.98)
MV	0.935**	0.323
	(2.15)	(0.66)
Vlt	-0.005	-0.006
	(-0.87)	(-0.81)
Adj-R^2	0.081	0.115

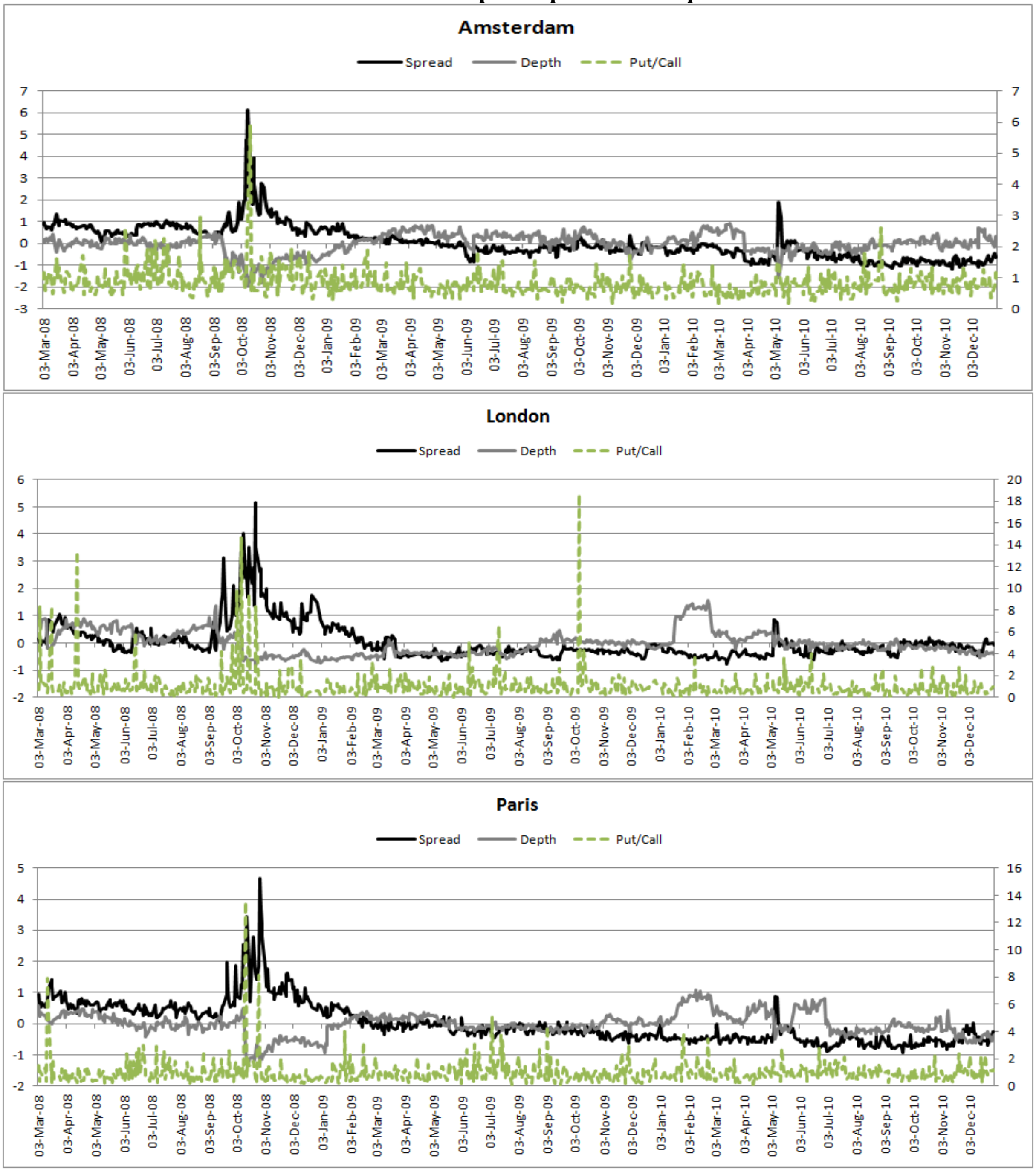
Notes: This table presents the results of the cross sectional regression of the proportion of variability explained by the first common factor for each asset against firm characteristics. The dependent variable refers to the Adjusted R^2 for each asset which is obtained by regressing the price-volume weighted spread against the first factor. *Fr* refers to the mean of transaction frequency. *OVlt* is the options trading volume per asset (scaled by 10^6) and *OPRV* refers to mean option realized volatility per asset. *PBAS* refers to the mean underlying proportional bid-ask spread per asset. *MV* refers to the mean market value per asset (scaled by 10^6). *Vlt* refers the mean underlying market volatility. T-statistics in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Table 5
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***
	(5.16)	(5.80)	(3.86)	(5.58)	(2.77)	(3.59)
Amsterdam call $_{t-1}$	-0.079	0.067	-0.104	-0.002	-0.166	-0.095
	(-0.86)	(0.80)	(-0.80)	(-0.02)	(-1.45)	(-0.81)
Amsterdam call $_{t-2}$	0.057	0.050	0.163	-0.034	0.065	-0.158
	(0.62)	(0.60)	(1.25)	(-0.27)	(0.56)	(-1.35)
Amsterdam put $_{t-1}$	0.156	-0.019	0.164	0.155	0.125	0.138
	(1.51)	(-0.20)	(1.12)	(1.09)	(0.96)	(1.05)
Amsterdam put $_{t-2}$	0.141	0.149*	0.117	0.214*	0.103	0.241**
	(1.55)	(1.81)	(0.91)	(1.70)	(0.90)	(2.08)
London call $_{t-1}$	0.148***	0.079	0.367***	0.298***	0.159**	0.066
	(2.63)	(1.55)	(4.62)	(3.85)	(2.26)	(0.93)
London call $_{t-2}$	-0.049	-0.001	-0.065	-0.013	-0.092	-0.067
	(-0.90)	(-0.02)	(-0.85)	(-0.17)	(-1.35)	(-0.97)
London put $_{t-1}$	0.008	0.015	0.237***	0.189**	0.031	0.005
	(0.14)	(0.29)	(3.01)	(2.46)	(0.45)	(0.08)
London put $_{t-2}$	-0.051	-0.068	0.081	0.097	-0.048	-0.110*
	(-0.98)	(-1.43)	(1.09)	(1.34)	(-0.72)	(-1.65)
Paris call $_{t-1}$	0.176**	0.216***	-0.047	-0.049	0.196**	0.220**
	(2.47)	(3.35)	(-0.46)	(-0.50)	(2.18)	(2.42)
Paris call $_{t-2}$	0.101	0.046	0.147	0.060	0.189**	0.148
	(1.47)	(0.75)	(1.52)	(0.63)	(2.20)	(1.70)
Paris put $_{t-1}$	-0.114*	-0.110*	0.036	0.016	0.246*	0.322*
	(-1.72)	(-1.84)	(0.38)	(0.18)	(2.95)	(3.83)
Paris put $_{t-2}$	-0.027	0.000	-0.175*	-0.142	0.107***	0.151***
	(-0.42)	(0.00)	(-1.87)	(-1.56)	(1.30)	(1.80)
R^2	0.175	0.197	0.366	0.307	0.447	0.455

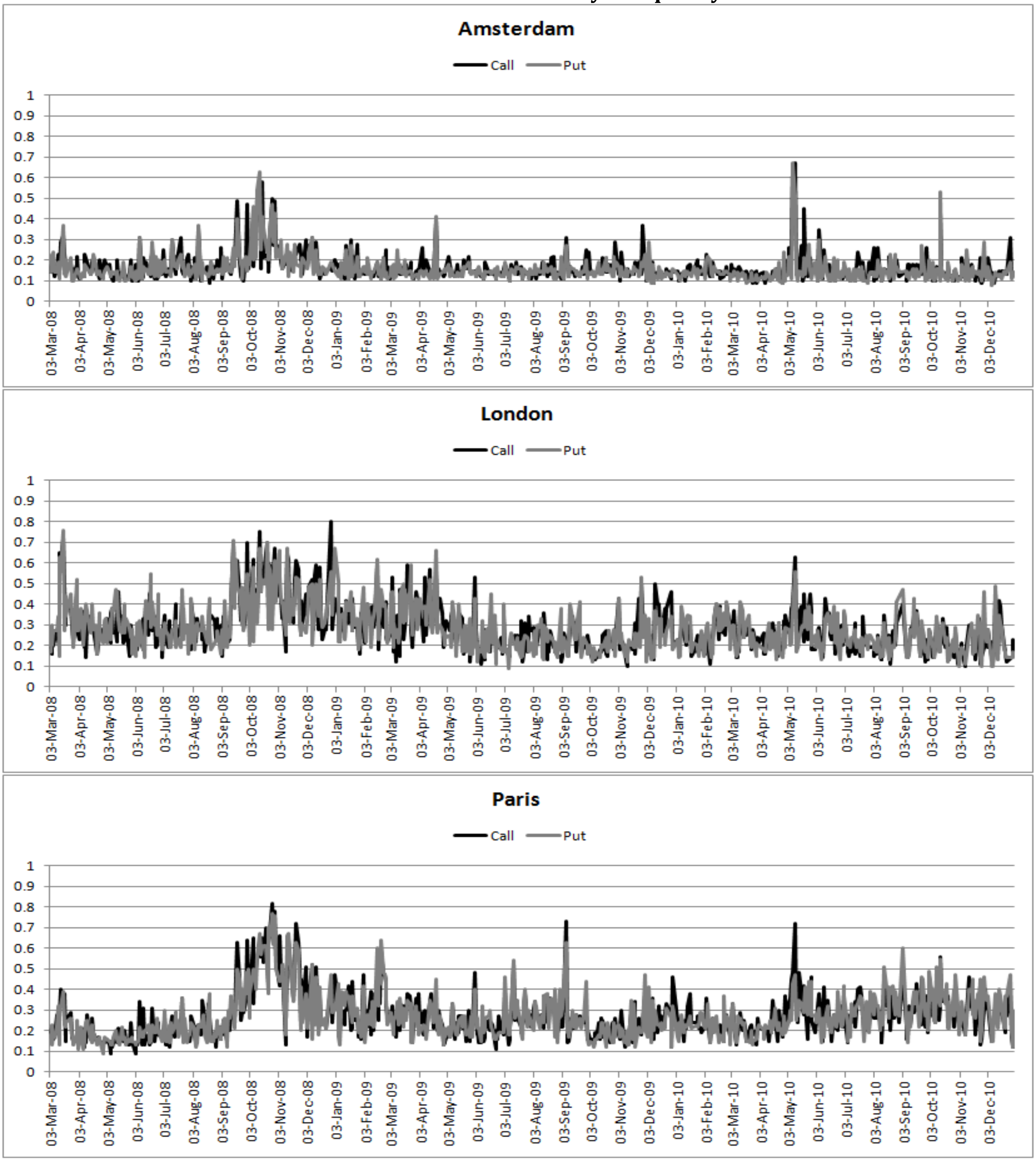
Notes: This table presents the VAR regression results for the proportion of variance explained by the principal common factor for each market, as specified in equation (6). T-statistics in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels, respectively.

Figure 1
Time series of option spread and depth



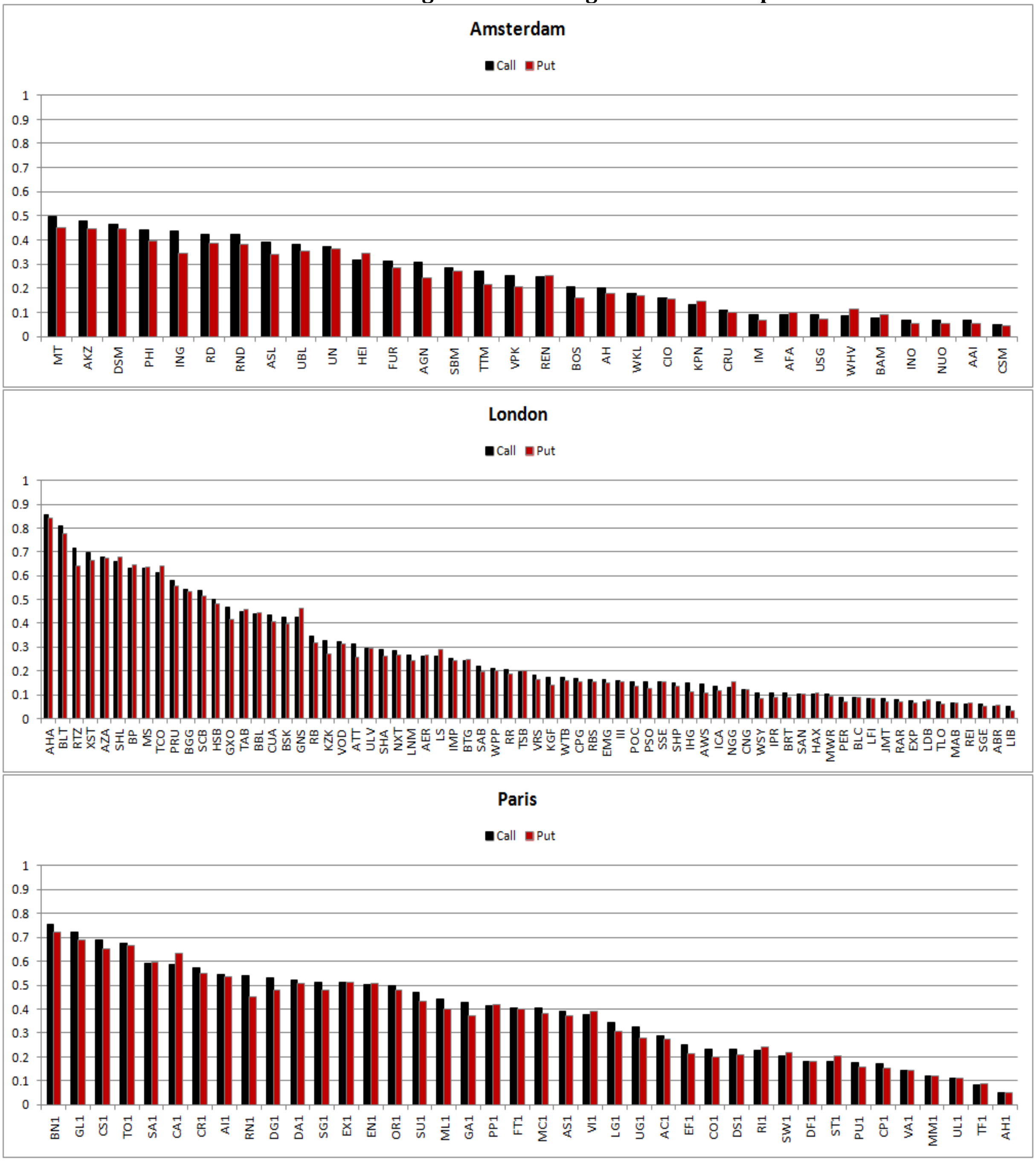
Notes: This figure presents the time series plots of individual equity options liquidity by exchange and contract type (right-hand y-axis). Each plot is constructed as the equal-weighted average of the daily average quoted spread and depth per trading day and ticker. The put/call ratio refers to the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

Figure 2
Time series of commonality in liquidity



Notes: This figure presents 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 presents 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.