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On the usefulness of intraday price ranges to gauge liquidity in cap-based portfolios☆

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ABSTRACT

We find that easy-to-observe price ranges are useful for estimating intraday liquidity. Following the literature on range-based volatility estimators, we go beyond the use of the closing price only and rely on the full range of prices. Based on high, low, opening, and closing (HLOC) prices, we show that a greater intensity in the price discovery process (as measured by the open–close range) and a higher level of price uncertainty (as captured by the High–Low range) lower ex-ante liquidity for small, mid, and large caps. Realized volatility (RV) fails to capture these effects. Although order books have become increasingly difficult to treat, there is some good news: it has never been easier to look at price ranges.

1. Introduction

The quick and accurate estimation of liquidity has always been a particular challenge in finance. In early research, liquidity was reduced to immediacy, i.e. the immediate conversion of an asset into cash at the best available price (Demsetz, 1968). As the literature on market microstructure expanded, a more comprehensive definition of liquidity was proposed. For example, Harris (2003) defines liquidity as 'the ability to trade large size quickly, at low cost, when you want to trade'. In this definition, four liquidity dimensions can be identified: immediacy, width, depth and resiliency. Given the multi-dimensional feature of liquidity, it has become particularly challenging to obtain a reliable snapshot of the dynamics of liquidity. An impressive body of research has indeed demonstrated that liquidity dynamics can be complex, all the more so in stressful market conditions when there is strong price uncertainty.

In the extant literature on high-frequency data, price uncertainty is traditionally measured by realized volatility (RV) which is considered as a highly efficient volatility proxy. Realized volatility is nothing more than the sum of squared high-frequency returns over a given sampling period. These squared returns are based on closing prices (or, better, on closing mid-quotes, to avoid the bid-ask bounce bias). We combine the literature on range-based volatility estimators with the literature on intraday liquidity to show that the inclusion of the highest, lowest, opening and closing (HLOC) prices observed during the day gives additional information on liquidity dynamics in the order book, beyond what realized volatility brings as explanatory power.

Reinvestigating the relationship between liquidity and volatility is worthwhile for the obvious reason that if price uncertainty is mis-estimated, market participants cannot evaluate the (liquidity) risk premium correctly and make wrong investment decisions. It is more likely to be the case when price uncertainty is only based on changes in closing prices because the variation in closing prices ignores two sources of uncertainty: the variations between the highest and the lowest price, on the one hand, and the variation between the last closing price and the next opening price, on the other.[2] As suggested by Fiess and MacDonald (2002), HLOC prices are particularly

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[2] Uncertainty is not defined in the sense of Knight (1921), i.e. a risk that is not measurable, but by the amplitude of total price variation between the low, high, open, and and close prices.

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appropriate to characterize price ranges, such as the magnitude of total price fluctuations or the occurrence of price gaps. The literature on range-based volatility estimators, that we briefly review in the next section, also confirms the usefulness of HLOC prices.

Range-based price movements include: the Open–Close (OC) range, the High–Low (HL) range, and an interaction variable (OCHL), i.e. the ratio of the OC to the HL ranges. All else equal, a large OC range indicates that the price discovery process is driven by strong buying or selling pressure, so that the price moves towards a new fundamental value. The HL range measures the total price movement. For a given OC range, a large HL range indicates that price uncertainty has been strong, without being necessarily captured by volatility which relies on closing prices only. The OCHL ratio measures the *relative* amplitude of the price movement beyond the Open–Close range. When the OCHL ratio is close to zero, the price discovery process is very much polluted by uncertainty that prevails around the true stock value. We investigate whether these three variables contain more information than price returns or traditional volatility measures with respect to both the price discovery process and the behavior of market participants. OC and HL ranges may indeed convey additional information than the simple return, which is computed on the basis of closing prices only. The HL range is also a measure of total price variation and is not equivalent to realized volatility, which is again strictly based on closing prices or mid-quotes. Finally, the OCHL ratio compares the magnitude of the price discovery process (OC range) to the total price movements (HL range): the lower the OCHL ratio, the lower the proportion of total price uncertainty that can be justified by the price discovery process.

The objective of this paper is to revisit the liquidity–volatility relationship by quantifying the information content of these price ranges for estimating liquidity. By testing several hypotheses, we show that these range-based measures of price dynamics are significantly related to liquidity. We address two questions in particular: How is intraday liquidity affected by the price discovery process (i.e. the OC range), the total price variation (i.e. the HL range), and the proportion of total price uncertainty that can be justified by the price discovery process (i.e. the OCHL ratio)? And does realized volatility encompass these range-based measures of price dynamics? Liquidity in the limit order book is measured by several book-based and trade-based proxies. Ex-ante (or book-based) liquidity is measured by the relative spread, the depth, slope, and dispersion in the order book. Ex-post (or trade-based) liquidity is measured by the number of buyer and seller-initiated trades, the total number of trades, the average trade size, and the trading volume. As control variables, we also include dummy variables related to the occurrence of zero returns, the bullish or bearish movement during the interval, and the occurrence of price gaps. [3]

We use Euronext intraday data on 300 stocks belonging to three different market capitalization classes (i.e. small, mid and large caps). The literature has provided valuable evidence showing that market capitalization has a direct impact on liquidity: Less liquid stocks often belong to the small-cap segment of the market. For each of these three cap-based portfolios, we study the sensitivity of each of the liquidity proxies to all the price movement variables defined above. We estimate the regressions on 15-minute intervals by OLS with adjusted standard errors. We further address this relationship by implementing the robust and median regression techniques that deal with the presence of outliers in the sample. We also investigate endogeneity issues by estimating a model of simultaneous equations. As a robustness check, we use 10-minute and 20-minute time intervals.

HLOC price ranges are found to provide additional information on the behavior of buyers and sellers and on the way liquidity evolves, even after adding realized volatility as explanatory variable. The results suggest that, whatever the liquidity dimension, HLOC price movements are informative to characterize liquidity dynamics. Positive changes in price ranges for both HL and OC ranges are related to negative variations in book-based (or ex-ante) liquidity proxies. All else equal, liquidity is further reduced when the OCHL ratio decreases, meaning that liquidity further decreases when the price discovery process is not smooth and accompanied by 'excess' uncertainty (i.e. by price variations that go beyond the OC range). Inversely, liquidity improves when the total variation observed during the interval does not differ much from the OC price range. In such a case, the price discovery is not plagued by 'excess' uncertainty. We also confirm the positive link between trade-based proxies (i.e. trading activity) and price uncertainty, in accordance with the literature on the volume–volatility relationship. We do not insist much on these findings since they are well-known. All in all, we conclude that the information content of HLOC price movements for intraday liquidity estimation is undeniably substantial, including for the small-cap portfolio.

The remainder of the paper is organized as follows. In Section 2, we describe the sample and the model specification. We also define all the liquidity and price movement variables used in the empirical section. We report the empirical findings and the robustness checks in Section 3. The final section concludes.

2. Data and methodology

We use tick-by-tick Euronext data for 61 trading days from February 1, 2006 to April 30, 2006. The database of 300 stocks is divided into three cap-based portfolios. Large, mid, and small caps respectively represent those companies with a market capitalization larger than EUR 1 billion, between EUR 150 millions and EUR 1 billion, and below EUR 150 millions. We include 100 stocks in each category based on their market cap at the beginning of the sample.

The use of this dataset presents two key advantages. First, we have information on the full order book, including undisclosed data on hidden orders and market members' ID. By using market members' ID, we are able to disentangle buyer-initiated and seller-initiated trades without any error margin. In many market microstructure studies, the Lee and Ready (1991) algorithm is used to categorize buyer and seller-initiated trades. Although this algorithm has proved to be relatively efficient, misclassification still occurs. In our dataset, there is none since we know the order that initiates the transaction. Second, we avoid the volume shift and market fragmentation that have been occurring since the implementation phase of MiFID. As today's trading environment is much more decentralized than before, more recent datasets are often less representative and less reliable. In a number of recent studies, there is often insufficient information on the level of trading activity that prevails on the competing Multilateral Trading Facilities (MTFs) and dark pools.

In the following two sections, we give more details on the various proxies that we use to characterize liquidity. By drawing insights from the literature on range-based volatility estimators, we also motivate the use of range-based price movements to better estimate liquidity. Finally, we state six hypotheses that will be tested in the empirical section.

2.1. Liquidity proxies

At the end of each trading interval, we calculate the relative (quoted) spread (*RS*) and the quantities outstanding at the five best limits (i.e. depth) for the ask side (*QA*), the bid side (*QB*), and the sum of the bid and ask (*Q*).

[3] Price gaps occur when the previous high (low) is below (above) the current low (high).