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Market liquidity as dynamic factors

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ABSTRACT

We use recent results on the Generalized Dynamic Factor Model (GDFM) with block structure to provide a data-driven definition of unobservable market liquidity and to assess the complementarity of two observed liquidity measures: daily close relative spreads and daily traded volumes for a sample of 426 S&P500 constituents recorded over the years 2004–2006. The advantage of defining market liquidity as a dynamic factor is that, contrary to other definitions, it tackles time dependence and commonness at the same time, without making any restrictive assumptions. Both relative spread and volume in the dataset under study appear to be driven by the same one-dimensional common shocks, which therefore naturally qualify as the unobservable market liquidity shocks.

1. Introduction

Liquidity is ubiquitous in financial practice and theory and has a pristine definition: an asset is *liquid* if it is easily convertible into cash, the reference asset with perfect liquidity. This definition is often rephrased in terms of time, volume, and cost. Indeed, *when people think about liquidity, they may think about trading quickly, about trading large size, or about trading at low cost* (Harris, 2003, p. 394). Since Kyle (1985), these three dimensions are well defined. The time dimension refers to *resiliency*—the speed with which pricing errors caused by uninformative order-flow shocks are corrected or neutralized in the market. Cost refers to *tightness*—the accepted price for immediacy in resolving the trade. Last, volume refers to *depth*—the volume that can be traded without price variations. See Minguet (2003), O'Hara (1998) or Schwartz (1993), among others, for further details.

Though the qualitative concept of liquidity is clear, its quantitative evaluation poses a major problem. Liquidity indeed is an unobserved variable, which implies that it has to be evaluated from the measurement of liquidity-related quantities or proxies, known as *liquidity measures*. But this is a delicate task because of the difficulty (i) to capture the three dimensions of liquidity in a single measure and (ii) to reach a consensus on the liquidity measures to be taken into account. This double difficulty seriously challenges the objectivity of any final assessment. The simplest liquidity measures currently considered in the empirical literature cover only one of the three dimensions. Trade durations, for instance, defined as time intervals between two trades, clearly carry liquidity-related information, but only cover the time dimension, ignoring tightness and depth. Moreover, they require tick-by-tick data: at lower frequencies (such as daily frequency), trade durations cannot be computed, as observations are regularly spaced.[1] Daily close or open bid–ask spreads, defined as the difference between the

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[1] Other measures of resiliency are possible, though. Dong et al. (2007) estimate resiliency as the observed mean-reversion parameter in the stock's pricing-error process (due to a shock in the order flow) via Kalman-filtering methods. The resulting estimate therefore is a model-based measure of resiliency that is not observed directly but a function of prices and volume (order flow).

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lowest ask and highest bid prices for an asset at some given point in time, measure liquidity effects as well, but mainly cover tightness. Daily realized volumes also measure the liquidity effects of an asset, but only cover its transacted depth. A number of papers have proposed measures that combine tightness and depth, such as the Hasbrouck and Seppi (2001) *quote slope*, the Domowitz and Wang (2002) *order book integral*, the Amihud (2002) ratio of average volume effect on absolute returns, or the Pastor and Stambaugh (2003) measure for average volume-related return reversal. The former two consider the existing shape of the available order book through time, while the latter rely on transacted prices and volumes. A common drawback of all those measures is that we do not know up to what extent they capture liquidity dynamics only. To get a deeper understanding of liquidity, we should study interrelations between the various liquidity measures and investigate their relation to liquidity. Literature on this subject is scarce, however, and most analyses are based on one single liquidity measure.

The same comments apply in the analysis of *market liquidity*, where the aim is to understand commonness in liquidity across securities. Chordia et al. (2000) and Hasbrouck and Seppi (2001) find that a common or "market" component is significantly present in various liquidity measures taken over a large cross-section of stocks. Amihud (2002), Eckbo and Norli (2002), Pastor and Stambaugh (2003) or Acharya and Pedersen (2005) find that market liquidity explains price differences across assets. The influence of these articles should not be underestimated, as they all substantially increase our knowledge and understanding of the role of liquidity in financial markets. However, they still rely on the choice of a single liquidity measure, without much of an analysis of its net informative contribution in explaining the market liquidity phenomenon. A first attempt to assess market liquidity based on several liquidity measures via principal component methods was made by Korajczyk and Sadka (2008); although based on an entirely different technical approach, our contribution is largely in the same spirit.

None of those previous contributions, indeed, fully exploits the time series nature of the data. In particular, they all overlook the leading/lagging phenomenons that may exist among the various liquidity measures and are particularly relevant here, since liquidity-related data are highly autocorrelated. Taking such time series features into account naturally brings the Generalized Dynamic Factor Model (henceforth GDFM) methods into the picture. These methods were developed in a series of papers by Forni et al. (2000, 2004, 2005), Forni and Lippi (2001), and Hallin and Liška (2007, 2011). They allow for disentangling commonness (market components) and idiosyncrasy (stock-specific components), not only across panels consisting of some given liquidity measure observed over a large number of stocks, but also across panels juxtaposing several such measures. Contrary to other dynamic factor methods (such as Stock and Watson, 2002a,b, or Bai and Ng, 2002), GDFM methods do not impose any restriction (beyond the usual assumptions of second-order stationarity, etc.) on the actual data-generating process.

We examine here the complementarity of two simple and widely used liquidity measures: daily close relative bid–ask spread and daily realized dollar volume, for 426 S&P500 listed stocks from January 2004 till December 2006. This is a period characterized by a "steady" state of market liquidity, which is appropriate for the scope of this study.[2] A period with extreme events and/or liquidity crunches, though important, would introduce distortions in the measurement of commonness, which are left for future research. It should be also emphasized that our analysis is based exclusively on observed market variables, and does not involve functions of those observed quantities, such as the Amihud (2002), or Pastor and Stambaugh (2003) measures. Contrary to volume and spread, which are primitive measures of liquidity, those measures, as well as those proposed by Dong et al. (2007), already are aggregates of prices and volume, aiming at a similar objective as we do. Therefore, there is no point in incorporating them in our analysis, as this only would distort the overall picture.

Our methodological tool throughout this paper is the method proposed by Hallin and Liška (2011) for the analysis of large panels with block structure, where the blocks represent the two subpanels of volume and relative spread, respectively. The Hallin and Liška method permits us to identify, estimate and compare the factors driving each subpanel and the factors driving the joint panel. In particular, it allows us to assess up to what extent commonality in volume coincides with commonality in relative spread. As volume and relative spread cover different aspects of liquidity (depth and tightness, respectively), they are a priori unlikely to carry exactly the same information: it could be that some features of liquidity are explained by realized volume but not by relative spread, and conversely. In GDFM terms, this means that some common spread shocks might a priori be idiosyncratic to volume and vice versa. Moreover, the analysis using GDFM takes into account the dynamic interactions between the two measures: some liquidity features indeed may be leading in volume while lagging in spread, and vice versa. Our analysis admittedly does not include a third subpanel with a measure of resiliency. Trade durations would be natural candidates; being of a tick-by-tick nature, however, they do not match the daily sampling features of our panels. Alternatives are possible, such as daily trade intensity (daily number of trades) series, but these are highly correlated with volume. The measure proposed by Dong et al. (2007) is another candidate, but it is model based and hence not a primitive measure of liquidity. This issue clearly deserves further investigation.

Our findings mainly go in three directions. First, it appears that the common relative spread and common volume spaces coincide, and have dynamic dimension one. This means that, although relative spread and volume cover different aspects of liquidity, their market or common components have the same origin and thus carry the same information. Moreover, that common space being one-dimensional, it is driven by a unique shock, which therefore strongly qualifies as the unobservable market liquidity shock. This suggests some market homogeneity with respect to liquidity, and that there should be no distinct liquidity effects originating, for instance, from different sectors or different types of investors. Second, on average, market-related shocks account for 12% of the total variation of a stock's relative spread and for 18% of the total variation of its volume. This may seem a rather low proportion, but is not surprising when compared to the variance decompositions obtained in Hasbrouck and Seppi (2001) and Chordia et al. (2000), even though we should be careful with such comparisons, given that databases and the nature of measures differ. Third, we observe a significant difference between idiosyncratic spread and volume correlograms. On average, idiosyncratic relative spread components are only weakly autocorrelated, but they are persistent. By contrast, volume components exhibit higher autocorrelations, with much faster decay. This difference can be explained by the fact that S&P500 constituents are highly traded stocks with thick limit order books. Relative spreads for such stocks do not move quickly, so that the impact of a market shock stays for long. Volumes, on the contrary, are more flexible, and their adaptation to changing market circumstances is much faster.

The outline of the article is as follows. Section 2 provides a short survey of the literature, and explains why the GDFM approach is more appropriate. In Section 3, we present the building blocks of GDFM. Section 4 gives information about the dataset used and comments on the liquidity measures considered. The main results are presented in Sections 5 and 6 concludes.

2 While allowing for serial auto- and cross-correlation, our methods indeed require second-order stationarity.