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Measuring the liquidity part of volume ☆

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ABSTRACT

Based on the concept that the presence of liquidity frictions can increase the daily traded volume, we develop an extended version of the mixture of distribution hypothesis model (MDH) along the lines of Tauchen and Pitts (1983) to measure the liquidity portion of volume. Our approach relies on a structural definition of liquidity frictions arising from the theoretical framework of Grossman and Miller (1988), which explains how liquidity shocks affect the way in which information is incorporated into daily trading characteristics. In addition, we propose an econometric setup exploiting the volatility–volume relationship to filter the liquidity portion of volume and infer the presence of liquidity frictions using daily data. Finally, based on FTSE 100 stocks, we show that the extended MDH model proposed here outperforms that of Andersen (1996) and that the liquidity frictions are priced in the cross-section of stock returns.

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1. Introduction

The use of total traded volume as a proxy for liquidity is well documented in the literature [see Gallant et al. (1992), Domowitz and Wang (1994), and Darolles and Fol (2014) among others]. However, recent studies support the idea that stocks with a high traded volume are not necessarily the most liquid ones. Indeed, the total traded volume can increase in response to both information and liquidity shocks. For example, Borgy et al. (2010) note that price-impact-based indicators are more accurate than raw traded volume for identifying liquidity problems in the currency exchange (FX) market. The flash market crash of May 6, 2010 is a good illustration of the simultaneous effects of information and liquidity shocks on traded volume. Recall that bad news concerning the European debt crisis resulted in sell-side pressures on U.S.-based product prices, thus increasing market volatility. In addition, buy-side liquidity in E-Mini S&P 500 futures contracts and S&P 500 exchange traded funds dropped sharply. In response to this situation, a large fund initiated a sell program for a substantial number of E-Mini contracts. This trading program was calibrated to target an order execution rate of 9% of the previous minute trading volume. This resulted in an extraordinarily high trading volume and further increased the feeding rate of automated executed orders for the considered fund, implying a liquidity crisis for both the E-Mini and individual stock markets. Consequently, during this day, at 2:42 pm, the DJIA Index had plunged by about 300 points, and by 600 more points at 2:47 pm (which resulted to an abnormal intradaily return of almost −9%) before recovering a few minutes after; by 3:07 pm, the market had regained almost 600 points. At the end of the traded day, the DIJA Index lost only 3% of its value which reflected bad news related to worries about the debt crisis in Greece. In contrast, the daily traded volume was more than twice as high as the average volume of the 30 past trading days. Three important lessons should be drawn from this event. First, using the total traded volume as a liquidity indicator can be misleading, especially in periods of significant volatility. In fact the total traded volume can increase in response to both information and liquidity shocks; observing an important traded volume does not necessarily mean that the market is liquid. It is thus important to be able to separate information from liquidity components of volume. Second, the volatility–volume relation, rather than volume alone,

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should be exploited to distinguish between information-based and liquidity-based trading and used to build more efficient trading algorithms. Third, understanding the determinants of total traded volume is not a trivial exercise; we must be able to model the respective impacts of information and liquidity shocks on trading characteristics.

This example leads to a natural question that determines the scope of this paper: how can we separate information from liquidity shock impact on the daily traded volume and thus measure the liquidity portion of volume? To answer this question, we develop an extended version of the mixture of distribution hypothesis (MDH) of Tauchen and Pitts (1983) that accounts for the presence of liquidity frictions. The standard MDH framework assumes that the market is perfectly liquid and that only information affects price changes and traded volumes. However, recent liquidity events suggest that we cannot address information shock impact on trading characteristics without considering liquidity frictions.

Distinguishing between the informative and non-informative portion of volume is not new in the literature. Andersen (1996) proposes an extended MDH version to separate the informed from the noise (or liquidity) trading components of volume. However, Andersen's definition of the noise trading component of volume is *ad hoc* and does not rely on any structural definition of liquidity trading.[1] In addition, Andersen's MDH version is difficult to calibrate, and its empirical validity is bounded when the model is tested using larger samples of data.[2] In contrast, the extended MDH version developed here is based on the theoretical framework of Grossman and Miller (1988), henceforth GM, which admits the presence of liquidity frictions within the trading day and is structured to explain how they impact the way in which information is incorporated into prices and volumes. According to GM, liquidity is determined by the demand for and the supply of immediacy. Two types of market participants are considered. The first type, active traders, trades in response to information shocks. The second type of trader acts as a market maker. They provide immediacy when the market faces liquidity frictions and liquidate their positions once prices return to their fundamental levels to obtain the liquidity premium. As discussed by Hendershott and Riordan (2013), in practice, algo traders who monitor the market, are not trading for information purposes so they can definitely be considered as market makers. Liquidity frictions result from temporary order imbalances due to trade asynchronization among the information-based traders. These order imbalances are resorbed by the market within the trading day. In fact, market markers manage their inventory position so as to get back home flat at the end of the day.[3] The GM framework implies that the liquidity frictions occurring at the intradaily frequency do not impact the daily price change. However, they increase the daily traded volume because the volume traded by market makers to liquidate their positions adds to the volume that would prevail in the absence of liquidity frictions.

In this paper, we first exploit the theoretical definition of liquidity frictions in the sense of GM allows us to put enough structure in the standard MDH model of Tauchen and Pitts (1983) to capture the impact of liquidity frictions on daily trading characteristics. Recall that the MDH models represent reduced econometric forms of microstructure models, thus facilitating the estimation of the information flow impact on the relation between price change and volume. The standard MDH model provides an explanation of the positive correlation between volume and squared price change at the daily frequency as well as other stylized facts, such as the fat tailed probability distributions of the daily time series of returns and volumes [see Harris (1982), Harris (1986), Harris (1987), Tauchen and Pitts (1983), among others]. The basic idea behind the MDH is that the joint distribution of daily price changes and volume can be modeled by a mixture of bivariate normal distributions conditioned by a unique latent variable, the information flow, which is supposed to be random. However, the standard MDH assumes that the market is perfectly liquid, disregarding the presence of liquidity frictions. From this perspective, we reconsider the standard MDH of Tauchen and Pitts (1983) by incorporating a second latent variable to capture the effect of liquidity frictions on daily traded volume. Our version of the MDH with two latent variables, called the MDHL model, allows us to exploit the volatility–volume relation to decompose the daily traded volume for a given stock into two components due to information and liquidity shocks.

Second, because our econometric specification can be tested empirically, we can filter the liquidity portion of total traded volume and infer the presence of liquidity frictions using the daily time series of returns and volumes. In particular, the model imposes restrictions on the joint moments of price change and volume as a function of only a few parameters. It is thus possible to use the generalized method of moments (GMM) procedure of Hansen (1982) to estimate model parameters and to test the model's global validity by forming overidentifying restrictions.[4] We provide a stock-specific liquidity indicator using daily return and volume observations.

The contribution of this paper is twofold. First, relying on the theoretical microstructure framework of GM, we extend the information-based standard MDH model to account for the impact of liquidity frictions on daily trading characteristics. The MDHL model suggests that the volatility–volume relation has two determinants, information flow and liquidity frictions and that their respective impacts on returns and volumes should be modeled differently. The former is incorporated into the daily price changes and traded volumes. The latter impacts intradaily price variations and volumes; it does not affect daily price changes but increases daily traded volumes. Second, the empirical estimation of the MDHL model allows us to exploit the volatility–volume relation in order to separate the total traded volume into two parts due to information and liquidity shocks. We propose a measure of the liquidity part of volume, thus providing a more accurate proxy for market liquidity for individual stocks. In particular, this information could be useful for practitioners, such as high frequency traders or fund managers, who want to hedge against liquidity risk or to track liquidity frictions to construct liquidity arbitrage strategies.

Note that, the standard MDH theory considers only informed agents with homogenous beliefs trading simultaneously after the arrival of each piece of information in a frictionless market. This implies that, at each point of time, the equilibrium prices reflect the fundamental value of the assets. However, this theory does not account for more complex interactions between traders having different trading motives, such as informed traders, noise traders and institutional arbitragers, nor does it account for the effects of sequential trading and the dispersion of beliefs among traders on the trading characteristics. In this context, three other theories building on the volatility–volume relation refine and complete the MDH framework by providing a better understanding of how information is incorporated in price changes and traded volume. The first one is represented by the sequential arrival of information

[1] The noise trading component of volume is simply (and arbitrarily) supposed to follow a time-invariant Poisson process in Andersen (1996).

[2] The empirical tests in Andersen (1996) are based on only five common stocks listed on the U.S. market. As discussed in Section 4 of this paper, Andersen's MDH version is rejected by the data for more than 50% of the common stocks listed on the FTSE 100 index.

[3] see Menkveld (2013), Fig. 2 and page 720.

[4] This procedure is initially used by Richardson and Smith (1994) to test the standard MDH model.

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