

LIQUIDITY RISK IN FRONTIER MARKETS – HISTORY, MEASUREMENT AND A NEW APPROACH

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INTRODUCTION

Liquidity is a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at a low cost, and without moving the price. This definition clearly exists, and functions more often than not in G-7 countries. In the rest of the world, however, a better definition of liquidity would be a market characterized by the ability to buy and sell securities with relative ease. Another definition that could be used in Frontier Markets is to define illiquidity – which arises when an asset or security cannot be converted to cash quickly – and say that liquidity is the opposite of same.

In all three definitions of liquidity, the concepts of price, and in particular, price discovery, play a role. There is no liquidity if no price can be found and if there are problems in the price discovery process, e.g., a market-clearing price for a trade is difficult to find; volume will fall or cease to be. It is our opinion, and one that is shared by a growing number of economists and quantitative researchers, that liquidity and liquidity risk are best investigated and understood by studying price, and possibly price and volume together, versus the standard practice of examining historical volume.

In what follows, we will quote from other index providers as to how they define liquidity for index construction purposes, and then describe how Thomson Reuters will determine the liquidity necessary to make an index

investible. We will also use the terms “liquidity” and “investibility” somewhat interchangeably throughout, though both terms can take on other meanings than what we’ll use here.

HISTORY AND MEASUREMENT

Most index providers measure liquidity in both the developed and developing markets by using volume. An example of this is S&P’s Frontier Markets liquidity definition quoted below:

Liquidity. All index constituents must have a minimum value traded of US\$25 million for the preceding 6 months, as of the data reference date prior to the annual index reconstitution. To ensure the largest liquidity possible, value traded from multiple listings is analyzed for each company. Only the listing with the highest liquidity is selected in the final round.

Days Traded. All index constituents must have traded 10 or more days over each of the previous six months prior to the rebalancing.

Both MSCI and FTSE also use volume as part of their liquidity screen, while also taking into account free float and market capitalization. None of the major providers of indices explicitly use price as part of their liquidity screen (at least in their published methodologies).

Our problem with the use of volume as a main marker of liquidity is the lack of discriminating



power volume has when you look for stocks that may be susceptible to liquidity freezes. As an example, in a recent paper by Pastor and Stambaugh¹, they could find no evidence of higher stock returns being tied to volume related liquidity effects of any kind. To quote from their paper, “The pricing results ... seem distinct from any pure [*volume related*] liquidity effects.” This is not what you want to hear if you are a fund manager who invests in a stock that has the risk of seeing liquidity dry up – since you would want (or expect) to be compensated for this risk by getting higher than average returns. Other academic studies have confirmed the work of Pastor and Stambaugh, i.e., the inconclusive nature of using volume alone or as the primary liquidity tool to identify either the liquidity premium or the liquidity risk of a stock. The major implication here for index construction is that using just volume and no price data runs the risk of offering a benchmark, or beta-generating index, that is not representative of securities a manager would buy given the potentially illiquid nature of some of the securities that would pass the volume screen *and* the associated inability of volume to identify a good return versus liquidity risk trade-off.

Work in the past two to three years that has built on Pastor and Stambaugh’s effort has shown that there *is* a liquidity premium investors can expect for holding potentially illiquid stocks, so investors are not chasing a white rabbit here. And in a recent presentation by representatives of Norges Bank², they concluded that the best way to capture a stock’s liquidity risk and its associated premium is by using variables related to *price impact*, as they seem to carry the most information. Therefore, in agreement with current research, Thomson Reuters will use

price related measures of liquidity in order to build its investible indices³.

A NEW APPROACH

The Thomson Reuters approach to liquidity measurement is based on the PhD thesis of its employee, Dr. Mark Labovitz⁴. The liquidity measure Labovitz proposes exploits the fact that stocks whose liquidities are the most sensitive to market liquidity are not necessarily those whose prices are the most sensitive to market liquidity.

What we mean by this is that the price movement of an illiquid security is sticky and not regularized. Also the response of the security to the market factor (or factors in a multi-factor model) is much more likely to be idiosyncratic. A major consequence of such a condition is the fact that the fitting of a generalized extreme value (GEV) model would be highly problematic, i.e., the lack of liquidity would result in the GEV model parameters not being able to converge either at all or outside of acceptable statistical limits.

Now, this is a nice mathematical fact but what is GEV and how does it apply to financial situations, in particular liquidity? In order to answer these questions, a very brief primer on GEV is supplied below:

For many of us, earthquakes, hurricanes, and stock market crashes are surprising phenomena following no rule, but careful analysis has helped to discover distributions (GEV distributions) that acceptably model these extreme events. If you measure the size of many people and plot the heights along the x-axis and the number of people at each height on the y-axis, you will discover a mathematical rule, likely the well-known bell-shaped curve of a normal distribution. Amazingly,

¹ L. Pastor and R.F. Stambaugh, “Liquidity Risk and Expected Stock Returns,” *Journal of Political Economy*, Vol.111, No. 3., 2003

² L. Chollete, R. Naes, and J. Skjeltorp, “What Capture Liquidity Risk: Order Based versus Trade Based Liquidity Measures.”

http://www.norges-bank.no/upload/14403/presentasjoner/liquidity_risk_presentation.pdf

³ Interested readers are referred to the following article as a good technical introduction to measuring liquidity risk via price and other variables – C. Acerbi and G. Scandolo, “Liquidity Risk and Coherent Measures of Risk,” *Quantitative Finance*, Vol. 8, No.7, 2008.

⁴M. Labovitz “Using Return Level As A Dependence Function In A Statistical Model for the Joint Distribution of the Extreme Values of Equities,” PhD Thesis (in progress), Department of Mathematical Sciences, University of Colorado Denver.



much real-life data follows the normal distribution and its cousins, which are well understood and easily computable. However, when looking for extremes, which are in the tails of distributions, you often find that in real life situations these tails are fatter (there are more extreme occurrences) than classical distributions predict. Extreme value theory (EVT) can be effective at modeling extreme events and in our liquidity case noted above this means that those securities that are more likely to have periods of illiquidity can be effectively modeled using EVT and GEV distributions.

When using EVT, the typical question one would like to answer is: “If things go wrong, how wrong can they go?” So the problem is to model these rare phenomena, which lie mainly outside the range of available observations. In such situations it is essential to rely on a well founded methodology. EVT provides a confirmed theoretical foundation on which we can build statistical models describing extreme events. Labovitz demonstrates an effective use of EVT and GEV distribution, as applied to liquidity, in his thesis and for the more mathematically-minded, that part of his thesis is quoted in the appendix to this paper.

CONCLUSION

The Thomson Reuters liquidity screen allows us to concentrate on the behavior of these extreme events – periods of illiquidity - which we think allows us to build better investible indices. They are better beta-generating indices because they will more accurately reflect the securities a manager would buy given the actual or perceived liquidity risk versus return trade-off. And, they are better benchmarks because the securities will be more representative of those an investment manager would actually hold.

Recent studies done on portfolio construction have focused on downside risk by using the variance of negative returns as a measure of risk, but that is really focusing on the central observations in their model, not the events in

the tails - what many people today would identify as being the *real* downside. It has been shown that allocating capital using an EVT assisted Value-at-Risk measure will lead to a more conservative allocation, because the resulting portfolio is designed to hedge against worst-case market conditions. We expect similar results with our indices because of the liquidity tests we will implement for our Frontier Market and other indices i.e., Thomson Reuters indices will be strong, durable, investible indices across countries, regions, and a variety of markets.



APPENDIX^{5,6}

Context for Reproduced Research: This dissertation focuses upon an alternative means to build dependence functions and factor models describing the joint distribution of equity returns. The model makes use of extreme value theory (EVT) which is one of the central technologies used herein. In this and the sections immediately proceeding it, the investigator is performing quality adjustments to the initial data set which included daily performance measures on nearly 80,000 publicly traded securities over a period of eight years. The impact of missing data, incomplete sets of observations and time series deemed too short is greatly reduced the number of equity series under consideration by the investigator. A guiding principle in making these data reductions is that the investigator is looking for general results (results applicable across many equities series) rather than results which are idiosyncratic to a few equity series. It is in this context which investigator conducted the research described below.

In the initial fit of parameters for non-time varying generalized extreme value distributions (GEV), the investigator observed a substantial number of instances in which the maximum likelihood estimation of the block maximum⁷ extreme series failed to converge in accordance with model fitting diagnostics. It is in search of an explanation to describe this behavior that the investigator pursued the research described below.

Liquidity

Examination of the return series shows that a value of 0 for the daily return was not uncommon. According to FactSet (Pers. Comm. [2007]), these are accurate observations and are not indicative of missing or poor-

⁵ Thomson Reuters would like to thank Mark Labovitz for granting Thomson Reuters a limited license to use this material in their white paper on liquidity. Mark Labovitz reserves the right to grant others solely at his discretion the right to use and reproduce this material.

⁶ *Extracted from:* M.L. Labovitz. 2008. Using Return Level as a Dependence Function in a Statistical Model for the Joint Distribution of the Extreme Values of Equities. PhD Thesis (in progress). Department of Mathematical Sciences. University of Colorado Denver. Copyright Mark L. Labovitz, 2008.

Later analyses performed by the author have resulted in changes in counts in certain tables. The tables reproduced here have not yet been adjusted to reflect these changes, which do not lead to any results which alter the author's conclusions or the use to which the author has put this piece of research.

⁷ A block maximum methodology groups the observations (in this case return) by say time period and then takes the maximum or minimum value in the group to represent the extreme for the group. In this research block minimums using a weekly or monthly block were studied.

quality observations. What does a 0 value for a daily return mean? Well, since a daily return is defined as:

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}}$$

where: R_t is the total return for time t

P_t is the price adjusted for corporate action at time t

Therefore, a return value of 0 suggests $P_t = P_{t-1}$. It is most likely in the event of substantial numbers of the daily values being 0 that little or no trading of the security had taken place. Such a circumstance is known as illiquidity. In the event of illiquidity "an asset or security cannot be converted into cash very quickly (or near prevailing market prices)" (Financial.Dictionary [2008]). A market-clearing price for a trade is not easily or typically as rapidly found for an illiquid equity as for a liquid one. The price movement of the illiquid equity is "sticky" and not as regularized; also, the response of the return to the market factor is likely to be much more idiosyncratic. In the context of this research a major consequence of such a result would be that the fitting of a generalized extreme-value (GEV) model would be problematic because, as is described in the next chapter, the method of parameter-fitting used in this research is a highly nonlinear, iterative search. The manifestation of this lack of liquidity would be the failure to converge to reasonable maximum-likelihood estimator (MLE) GEV parameters (as defined by Smith [1985] and reported in Chapter 1) or to converge at all.

The GEV model-fitting activity will be developed in detail in Chapter 4. However, to look at the relationship between the distribution of zeros in the extreme-value series (liquidity) and the ability to estimate MLE-property-confirming estimates, the investigator ran non-time-varying estimates (once again discussed in Chapter 4) of the GEV location, scale, and shape parameters for weekly and monthly extreme-value series, constructed using the block-maxima model for all 15,528 equities resulting from the filtering detailed in Table 3.3. If the equities did not converge or did converge but did not meet the criteria laid out by Smith (1985), reproduced here for convenience, then a random variable ascribing the successful fit of the equity was assigned the value of 0. On the other hand, a successful convergence meeting the Smith criteria was assigned a 1:

- If $\xi > -0.5$, MLE_{GEV} estimators possess common asymptotic properties.
- If $-1 < \xi < -0.5$, MLE_{GEV} estimators may be computed, but they do not have regular or standard asymptotic properties.
- If $\xi < -1$, MLE_{GEV} estimators may not be obtained.

Additionally, the investigator created a number of independent variables from the analysis of the extreme weekly and monthly series. These were:

- Largest number of consecutive zeros (Max.Gap)
- The percentage of zeros in the extreme-values series (Portion.Zero)
- The number of “zero gaps,” namely, the number of sets of consecutive zeros separated by sets of one or more non-zeros (Num.Gaps)

The dependent random variable describing GEV model quality was modeled as a function of the functions of the sets of zeros, using a logistic regression model (Neter *et al.* [1996]).

Table 3.5 Analysis of deviance table from stepwise logistic regression for weekly extreme-value series

Source	Df	Deviance	Resid.Df	Resid.Dev	P(Q>=q)
Intercept	NA	NA	15,527	13,889.15	NA
Portion.Zero	1	7,747.07	15,526	6,142.08	0
Num.Gaps	1	458.05	15,525	5,684.03	0
Portion.Zero X Num.Gaps	1	125.55	15,524	5,558.48	0
Max.Gap	1	60.02	15,523	5,498.46	9.44E-15
Portion.Zero X Max.Gap	1	82.96	15,522	5,415.50	0

Table 3.6 Analysis of deviance table from stepwise logistic regression for monthly extreme-value series

Source	Df	Deviance	Resid.Df	Resid.Dev	P(Q>=q)
Intercept	NA	NA	15,527	10,349.14	NA
Portion.Zero	1	9,170.26	15,526	1,178.88	0
Max.Gap	1	61.59	15,525	1,117.29	4.21885E-15

Table 3.7 Cross-tabs from the assignment of weekly extreme-value series to classes

	Pred.Failed	Pred.Converged	Total Row
Obs.Failed	2,014	599	2,613
Obs.Converged	730	12,185	12,915
Total Column	2,744	12,784	15,528

Table 3.8 Cross-tabs from the assignment of monthly extreme-value series to classes

	Pred.Failed	Pred.Converged	Total Row
Obs.Failed	1,487	117	1,604
Obs.Converged	69	13,855	13,924
Total Column	1,556	13,972	15,528

The predictor selection method was a stepwise process using both forward and backward steps. The results (not shown here) exhibited a strong inverse relationship

between conversion and liquidity measures. Tables 3.5 and 3.6 are analysis of deviance (AOD) tables from the logistic regression for weekly and monthly extreme-value series, respectively. For both series the coefficients of the predictors are significant at small values of p. Also, for both series the portion of zeros found in a series played a leading roll in convergence.

Tables 3.7 and 3.8 are cross-tabs relating the observed convergence and failure to converge (denoted as Obs.Converged and Obs.Failed, respectively) to the predicted convergence and failure to converge (denoted as Pred.Converged and Pred.Failed, respectively). The predicted classification was created by thresholding the predicted probability at 0.5. This value was chosen by the investigator because there was no information to suggest reducing the uncertainty in a particular direction. Furthermore, when the investigator tried a series of threshold values on either side of 0.5, it was the misclassified cells that changed the most, swapping values in a direction dependent on the direction of the movement of the threshold away from 0.5. The correctly classified cells remained fairly constant under this examination. When the monthly and weekly datasets were examined separately greater liquidity was seen in the monthly series, with 13,857 liquid series versus 12,185 for the weekly series. Further, all securities found in the weekly liquid set were also in the monthly liquid set. (This result supports the view that increasing the number of zeros in the set increases nonliquidity, which in turn provides a degenerative extreme-value distribution, certainly under the block-maxima method.)

Note that every monthly series having a maximum of zero over a given month resulted in four or five zeros in the weekly series. Not only were the illiquid series problematic for extreme-value parameter estimation, their existence contradicted the consequences of the efficient market hypothesis (Fama [1965]). Therefore, other idiosyncratic behavior could have been expected from them, particularly when modeling joint distributions of uncertainty. The investigator, therefore, decided to reduce the useable universe of equities for further study to the 12,185 securities observed and predicted to converge in the cross-tabs of the liquidity analysis of the weekly extreme-value series.

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