September 2008

Northfield News

A Newsletter for the Friends and Clients of Northfield Information Services

Special Points of Interest:

- Main Article: Estimation of a Global Liquidity and Trading Cost Model
- Asia Seminars-Tokyo, Singapore, Sydney, Hong Kong
- Annual Conference Announcement– Venice Italy

Inside This Issue:

Estimation of a Global Liquidity and Trading Cost Model

By Dan diBartolomeo

Introduction

During August of 2007, stock markets around the world experienced extremely unusual return events. Numerous funds that had experienced losses in mortgage securities were forced to sell equity securities to meet margin calls, creating a dramatic imbalance between the number of willing sellers and buyers for some securities. This lead to falling prices for some equities and another cycle of margin related forced selling. Since these events, investors, particularly those with a quantitative approach to investment decisions, have been focusing on liquidity concerns.

There are a number of other market trends that are creating the need for a better understanding of how liquidity imbalances translate into trading costs and their impact on market prices. Algorithmic trading methods, which require an explicit forecast of market impact, continue to garner an increasingly large share of trading volume in developed markets. In addition, investors are increasingly participating in "frontier" markets with very low liquidity levels causing severe capacity constraints on the amount of capital employed. Finally, the growth of hedge funds has increased trading volumes dramatically, as these funds average something more than five times the turnover that traditional funds do.

There is an extensive amount of literature on how to predict the extent to which the introduction of a trade of a particular size will impact prices of a stock. Numerous models exist both in the academic literature and within the practitioner community. *However, empirical estimation and validation of such models has been published only for US data, with essentially nothing available on other global stock markets.*

This paper will attempt to contribute to this area of research in three ways. First, we will propose a particular functional form for market impact models that we believe has certain important advantages over the models currently available to practitioners. We will also illustrate the empirical estimation of this model. Secondly, we will introduce a very simple method for extending any existing model of US trading costs to any market around the world, particularly those with very low liquidity levels. Finally, we will introduce a method for estimating this class of models from "tick data" that is available for all global markets.

Discussion of Trading Costs

The essence of a traded asset's liquidity hinges on the cost of trading a particular quantity of that asset. The question is not really about whether you can trade, but rather how much change in the price must be absorbed in order to induce other market participants to take the other side of the trade you wish to do. We refer to this required change in price as *market impact.*

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Northfield Asia Seminar Series – Research on Investment Management and Risk
Hong Kong • Singapore • Sydney • Tokyo

Northfield will be hosting four one day seminars in Hong Kong, Singapore, Sydney and Tokyo. The purpose of the seminars is to showcase our research on various topics in investment and risk management to our growing list of Australian and Far East clients and prospects.

Hong Kong:
November 17, 2008, 9:00 am - 4:30 pm ● Landmark Mandarin , Central, Hong Kong

Singapore:
November 21, 2008, 9:00 am – 4:30 pm ● The Fullerton Hotel, Singapore

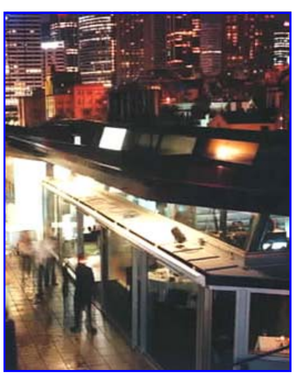
Tokyo:
November 26, 2008, 9:00 am - 4:30 pm ● Mandarin Oriental, Nihonbashi, Tokyo

Sydney:
December 3, 2008, 9:00 am - 4:30 pm ● The Quay Restaurant, The Rocks, Sydney

Tentative Agenda:
The detailed agenda will be finalized in the coming weeks and posted to the Northfield website. There will be a total of seven presentations. Check http://www.northinfo.com/events.cfm for the final agenda.

- A New Metric for Measuring Skill from Investment Performance
- Global Liquidity and Transaction Costs
- *To Be Determined*
- *To Be Determined*
- Short Term Risk from Long Term Models
- The Equity Risk Premium, CAPM and Minimum Variance Portfolios
- Twelve Questions Your Risk Management Tools Should Help You Answer

Contact Nick Wade in Tokyo if you would like to attend, +81 3 5403 4655 or e-mail: nick@northinfo.com.



Quay Restaurant, Sydney

Mandarin Oriental, Tokyo

Landmark Mandarin, Hong Kong

The Fullerton, Singapore

2009 Northfield Annual Research Conference

The Westin Excelsior, Venice Lido Resort • Venice, Italy • June 1-3, 2009

We are pleased to announce our 22nd annual research conference at the Westin Excelsior, Venice Lido Resort in Venice Italy.

The conference will officially begin on Monday, June 1st and end on Wednesday, June 3rd.

Further details and the complete conference agenda will be posted on the Northfield Website at **http://www.northinfo.com/events.cfm** as they become available. Registration is not currently open.

Contact Kathy Prasad at 617.208.2020, **kathy@northinfo.com** for more information.

Westin Excelsior, Venice Lido

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When we consider the overall cost of trading an asset, there are several components. The first is agency costs, the fees charged by brokers, exchanges and custody banks for actually executing the transaction. The second is bid/asked spread, the value difference between the prices at which liquidity providers such as market makers and exchange specialists are willing to buy and sell. The third component is the aforementioned market impact, the extent to which my trade requires change in the asset price in order to execute the desired quantity. The fourth cost is what traders call trend cost, or what portfolio managers might think of as *risk*. It is simply the price change that occurs due to the trading of other market participants between the time when I decide to trade and when my trade is actually executed. It should be noted that trend costs may be negative (a price may move in my favor).

There are two often overlooked ingredients to trading costs. The first is the issue of cross-market impact. If I am buying a large amount of a particular stock, say General Motors, my trade will impact the price of GM. To the extent that the relative value of other similar stocks such as Ford or Toyota are estimated by investors in comparison to GM, the market price of Ford or Toyota may also be impacted. Finally, we must also consider the opportunity costs of the time it takes to execute our transactions. Unless we are investing passively, we want to buy stocks before they go up, not after. Similarly, if we're selling we want to sell before they go down, not after.

In framing a discussion of liquidity and market impact, we always consider the dimension of time in the context of whether market impact is permanent or temporary. If our trades in any given stock are far apart in time, price movements caused by our trades will be independent of one another. If our trades follow each other with little time in between, market impact effects will have a cascading effect as each trade moves the price from where the previous trade left it. We call this persistent portion of market impact *stickiness*, and account for it in deciding how quickly to trade.

One way to think of the issue of market impact permanence is to build on the concept of a *participation rate*. For example, if we trade a stock in a quantity that is 5% of a typical day's trading volume, that trade will represent 2.5% of the expected volume over two days, 1.25% of the expected volume over four days and .5% of the expected volume over ten days. Eventually, the price influence of our trade exponentially decays to zero.

The empirical estimation of trading costs is difficult. Agency costs are essentially known in advance. Bid/Asked spreads are reasonably stable under normal market conditions but can widen substantially in periods of market stress. The determinants of variation in bid/asked spreads have been well explored in Menya and Paudyal (1996, 2000) and Chorida, Roll and Subrahmanyam (2000).

Market Impact Basics

An extensive array of market impact models have been proposed in the academic literature and brokerage firms. Among these are: Almgren and Chriss (2000), Ferstenberg (2000) and Cox (2001). Most models take the form:

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(Estimation, continued from page 3)

$$E[M] = \alpha S^{\pi} \qquad (1)$$

Where

E[M] is the expected value of the price movement in %

S is the quantity of shares to be traded

α, π are parameters fitted from empirical data

In most models, the α parameter varies stock by stock and represents the different levels of liquidity across stocks. The π parameter is typically singly estimated for an entire market. It has been speculated that the π parameter may different from market to market due to differences in exchange structure, the balance of institutional versus individual investment in stocks and the existence of alternative trading venues such as electronic crossing networks. Most studies suggest values for π of either one or one half. *It should also be noted that we can easily scale the α parameter to rescale the size of the trade S into units of percentage of expected daily volume, as traders often prefer.*

In order to accommodate models of this kind, the optimization software our firm makes commercially available allows for either popular value of π, or a weighted combination of the linear and square root processes:

$$M = [(B_i * S_i) + (C_i * |S_i^{0.5}|)] + \ldots \qquad (2)$$

We can also think of these two coefficients, B and C as being a weighted representation of the α parameter. These coefficients represent the *elasticity of the asset price with respect to trade magnitudes and hence are the true representation of liquidity.*

$$B_i = W * \alpha$$

$$C_i = (1-W) * \alpha$$

Market Impact for Dummies!

Unfortunately, when the available market impact models were utilized with the software, bizarre results were sometimes observed. For example, one model predicted that to sell 10% of the shares outstanding of a US small cap stock (market capitalization $500 million), the expected trading cost would be over 100% of the value. We believe these results arose because the model coefficients were based on empirical estimations from data sets that did not contain large trades because traders considered them too costly. Coefficients for B and C must be estimated under boundary conditions that provide rational results in the entire range of potential trade size from zero to all the shares of a firm.

Traders are very concerned that market impact effects are driven by information leakage. Once liquidity providers know what a particular investor is doing in terms of buying or selling particular securities, they will reset the prices at which they are willing to transact in order to maximize their profits. Let us consider a hostile takeover as the "worst case" scenario for market impact: we're going to buy up all the shares of a company and tell the entire world we're doing it. The takeover premium can be viewed as an extreme case of market impact. If we believe *only in the linear market impact process*, we can set our coefficient to the expected takeover premium for a stock divided by shares outstanding. If we believe *only in the square root process* for market impact, we can set our coefficient to the expected takeover premium for a stock divided by the square root of shares outstanding. If we don't know which process to believe in, we can just do both with a weighting summing to one.

$$Bi = W * (E[P_i] / S_i) \qquad (3)$$

$$Ci = (1-W) * E[P_i] / (S_i^{0.5}) \qquad (4)$$

B_i = the coefficient on the linear process
C_i = the coefficient on the square root process
P_i = the takeover premium in percent
S_i = the number of shares outstanding
W = a weight estimated from empirical data

To turn this simple estimation into a more complete model, we incorporate two additional features. First, we must consider differences in liquidity across different stocks. Secondly, we must recognize that our model based on takeover premiums represents the boundary condition of a "worst case" scenario for information leakage. Normal trading involves much smaller information leakage effects. If we assume takeover premiums are lognormal, we can easily express the expected takeover premium as a function of a liquidity measure

$$E[P_i] = QP / ((1 + K/100)^{Z_i}) \qquad (5)$$

P = % average price premium in a hostile takeover
K = the log percentage standard error around P
Z_i = the Z score of a liquidity measure for stock I
Q = a scalar between zero and one

Let us do a quick example with some stylized facts:

Various academic studies using M & A databases have reported average takeover premiums from 37 to 50% with a standard deviation around 30%. We will consider a hypothetical company with $5 billion market cap, $50 share

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(Estimation, Continued from page 4)

price and 100 million shares outstanding. Assuming P = 37, K = 40, W = .25, Z_i = 0, we would get a cost of 2.88% for a 1,000,000 share trade impact = 2.88% and .27% for a 10,000 share trade.

Implicit in this estimation is that the trades are done over a time period which is comparable to the time period over which stock prices react to the release of the news of hostile takeover (perhaps a day or two). To the extent we trade more slowly over a longer time period, the market impact costs would be reduced.

Estimating "Takeover" Market Impact Empirically

If we take our estimates of the P and K parameters from the finance literature on hostile takeovers, we need only estimate the Q and W parameters relative to whatever fundamental information we wish to use as Z. In order to facilitate empirical estimation, a dataset of actual trades was obtained from Instinet. This data set included over 1.5 million orders over an 18 month period with fine detail such as time stamps, arrival price, execution price, order type (buy/sell, limit/market), tracking of cancelled orders, etc. The information was anonymous. We have no information on what firms traded or which orders belong to whom. Almost all of the data was from the US, with some small representation of major markets such as Japan, UK, Canada, etc. Obviously this is a very large data set over which to estimate a model with only two free parameters.

We choose to explain the differences in liquidity levels across stocks using three characteristics: the log of market capitalization of the stock, the ratio of average daily volume to shares outstanding, and the inverse of the security's volatility. Each of these three characteristics is standardized into a Z-Score across our estimation universe of US stocks, and then the three values are combined in a weighted average.

Our final preparatory step is to define how we are going to measure the market impact of individual trades. One way to measure market impact would be to compare the price we got on our trade versus the price on the previous trade as a measure of how much our trade "moved the price." However, this measure may not be relevant to us. We care about how much the price moved from the price it was at when we decided to trade the stock, which we call the *arrival price*. It's the percentage in price between the execution price and the price that existed in the market when we got the order to transact the stock. This representation is consistent with the concept of "Implementation Shortfall" described in Perold (1988).

A grid search method was employed to identify the "best fit" values of Q and W over a set of 1.2 million US market orders. The choice of the Q and W pair was based on the trade dollar weighted goodness of fit (R-squared) and the requirement that the model not exhibit statistically significant bias (i.e. the average forecast has to fit the average cost). Unlike an OLS regression, the grid search does automatically produce a best linear unbiased estimate. We chose to use a trade dollar weighted R-squared as traders obviously care a lot more about getting this right when doing million share trades as compared to hundred share trades. The dollar weighted time interval between arrival of an order and its termination (either filled or cancelled) was approximately ninety minutes, illustrative of the fact that large institutional orders were involved.

If we continue our use of 37% to represent P, the central tendency of the takeover premium, we obtained a best pair of Q = .594 and W = .650. The trade dollar weighted R-squared was 74%. The R-squared values were fairly insensitive to the choice of Q and W and other combinations also produced very high degrees of fit.

Estimating Liquidity Globally using our US Model

Unfortunately, our Instinet trade database contained insufficient observations on non-US markets to proceed with the above model. In order to extend our results to other stock markets we would have to use other methodologies.

Our first effort to extend our results to global markets is based on the hypothesis that one of the observable manifestations of illiquidity is positive serial correlation in high frequency returns. The simple intuition is that when information arrives to the market that changes the value of a stock, limited liquidity will not permit everyone who wishes to transact to do so in the initial period following the news. Some people have to transact in the second and subsequent periods, inducing positive serial correlation to the returns. A more formal rationale for this effect is presented in Getmansky, Lo and Makarov (2004).

There are numerous statistical methods for the estimation of serial correlation, including autoregressive models and variance ratio tests. Due to the lack of normality in high frequency returns as described in diBartolomeo (2007), we chose to use a non-parametric "runs" test (Wald-Wolfowitz). The logic is simple: if a stock trades liquidly, there should still be a roughly 50% chance it will go up or down tomorrow, irrespective of whether it went up or down today. We should see the sign of daily returns change 50% of the time from one day to the next. If the trading is illiquid, the number of sign changes will be less than 50%.

(Estimation, Continued from page 5)

To extend our model, we first created a "seed sample" of US stocks broken into ten deciles of market capitalization. The sample included over 1500 random stocks ranging all the way down to very illiquid shares traded on the NASDAQ "Bulletin Board" and in the "pink sheets." For each group, we calculated the average Z value of the members for the US market impact model presented above, and produced an estimated average cost to trade 1% of shares outstanding in one trading day. We chose to use 1% of shares outstanding, rather than a percentage of average daily volume because for some of the illiquid stocks, the number of shares traded is so small that a small percentage of that value would be imperceptibly small to an institutional investor. These values are presented on the center column of **Table 1**.

Table 1

Market Cap Deciles	Cost for 1% Shares Out Trade in One Day	Avg. # of Return "Non-Changes" in 200 Days
1	.77	97.15
2	.97	100.75
3	1.15	98.07
4	1.28	100.94
5	1.46	101.77
6	1.71	105.29
7	2.00	107.48
8	2.44	111.03
9	3.32	112.56
10	4.98	117.49

We then calculated 200 trading days of daily returns for each stock for a period ending in July of 2008. The number of sign changes for the daily returns was counted. If a stock return was zero for the trading day, this was considered a "non-change" in the sign of the return. The average number of non-changes in return sign is also presented in **Table 1**. Obviously, there is a strong relationship between the expected costs from our model and the average number of return sign "non changes." An OLS regression of the two data sets yielded the equation below, with an R-squared of over 90%.

$$Y = -0.1716 + 0.0018X \qquad (6)$$

Where

Y is the fitted value for the estimated cost of a 1% of shares outstanding trade in one day

X is the average number of daily return sign non-changes in 200 trading days

Our next step was to take a sample of approximately forty-five hundred stocks in sixty-seven non-US countries. For large developed markets, we broke the stocks into three categories of capitalization (large, medium, and small) and took a random stratified sample for each category (equal numbers of stocks within each group within a country). Small countries were broken into two categories (large, small) and very small markets (less than 50 issues traded) were kept as one category. We then calculated the number of return sign "non-changes" in the same fashion as for the US. It was then possible to use the equation above to calculate the expected cost for trades according to our model. In **Table 2**, we present data similar to **Table 1** but for some groups of non-US stocks.

Table 2.

Category	Fitted Cost for 1% Shares Out Trade in One Day	Avg. # of Return "Non-Changes" in 200 Days
Australia Large Cap	1.71	103.6
Canada Small Cap	1.98	105.1
Columbia	6.97	132.5
Finland Small Cap	2.94	110.4
Mexico	3.66	114.3
Netherlands Large Cap	1.49	102.4
Bahrain	13.2	166.2
Switzerland Large Cap	2.13	105.9
Iceland	8.04	138.4
China	3.28	112.2

There is considerable heterogeneity in terms of the "non change" levels within stocks in the various groups. We are currently considering a refinement using Bayesian methods wherein the mapping of a given non-US stock into our US cost model will include a weighted average of the number of sign "non changes" at both the group and at the individual stock level.

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(Estimation, Continued from page 6)

Using Tick Data to Estimate Global Liquidity

Our second approach to estimating global liquidity is to use tick data to estimate an equation similar to equation (2)

$$M = [(D_i*I_t) + (E_i*|I_t^{0.5}|)] + \ldots \qquad (7)$$

Where

I_t = the imbalance between "buyer" and "seller" volume as a % of total volume

We adopt the model of Lee and Ready (1991) for our definition of "buyer" and "seller" trading volume. They assume that if a trade occurred on an uptick in price this was a buyer initiated trade that was accommodated by a liquidity provider. If a trade occurs on a downtick in price, they assume that this was a seller initiated trade that was accommodated by a liquidity provider. If a trade occurs on a flat tick (no price change) it is assumed to be of the same character as the previous trade.

Our data consists of every tick for the past twelve years of trading on the same sample of six thousand stocks used in the serial correlation method above. The data was obtained from Reuters. It must be noted that the Reuters data is organized by RIC code, so if a stock is traded at more than one venue (e.g. multiple exchanges), the trading at each venue will be treated separately and may require consolidation. The data set also includes every quote. The combined size of the entire Reuters tick data set for all securities worldwide approaches three hundred terabytes. The computational effort associated with using the tick data method is considerable.

To estimate coefficients D and E, we estimate equation (7) using daily returns as the dependent variable. The daily observations are weighted by the total trading volume for that day. Observations with negative imbalances have both side multiplied by negative one so as to avoid the need to take the square root of negative numbers. The estimation of coefficients is accomplished by taking the rank correlation relationship. Note that the rank correlation of the dependent variable with both imbalance and square root of the imbalance will be the same. The rank correlation values are then scaled by one half times ratio of the standard deviations of the dependent and independent variables to obtain the equivalent of regression beta coefficients.

Table 3

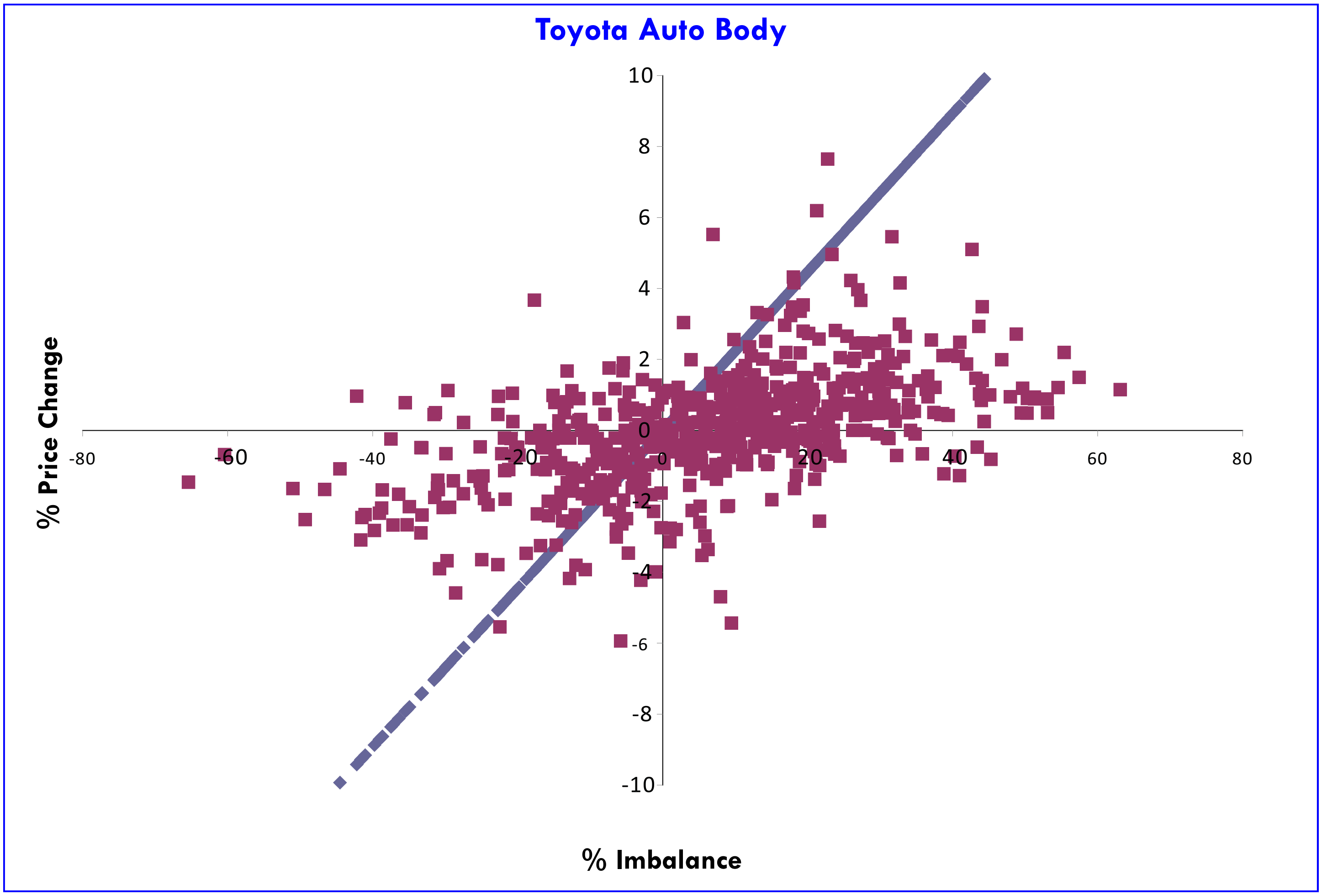
% Market Impact				
Name	R-Squared	2% I	4% I	10% I
TOYOTA AUTO BODY	0.153	0.330	0.495	0.872
ALL-AM SPORTPARK	0.175	3.195	4.705	8.026
BK OF MONTREAL	0.070	0.177	0.266	0.468
CARIBBEAN AMER	0.228	3.991	5.877	10.022
CHEROKEE INTL	0.047	0.302	0.447	0.769
DREAMS	0.170	0.573	0.843	1.437
GOOGLE	0.083	0.563	0.870	1.606
GRILL CONCEPTS	0.089	0.323	0.476	0.813
IMATION CORP	0.025	0.213	0.322	0.572
LINUX GOLD CP	0.171	0.741	1.096	1.883
METLIFE INC	0.091	0.291	0.440	0.784
MORNING STAR	0.222	0.415	0.592	0.954
REEDS	0.104	0.845	1.246	2.131
SPO MEDICAL	0.177	2.363	3.477	5.918
TIGER RENEWABLE	0.310	1.275	1.876	3.193
TERRA SYSTEMS	0.191	1.163	1.709	2.905
VIPER NETWORKS	0.158	1.579	2.323	3.955

A small sample of global firms is presented in **Table 3** with the R-squared of the relationship and the fitted values for imbalances of 2%, 4% and 10% respectively. To estimate cost of trades, a practitioner would merely estimate the expected imbalance as their contemplated trade as a percentage of average daily volume. The "noisy nature" of the relationship is illustrated for one stock in **Figure A** **(see top of next page)**.

While the tick method is normally estimated based on percentage imbalance of daily volume, we can rescale the imbalance values by the relationship of average daily volume to shares outstanding. In this way, we can convert equation (6) to equation (2) and obtain alternative estimates of those coefficients and work back to revised values for Q and W.

Conclusions

There are a variety of trends in today's global stock markets that are creating large amounts of concern about liquidity. For the purposes of investors, we believe the correct way to view liquidity is as the degree of price change which may be expected from the initiation of a trade of a given magnitude. Existing models of liquidity have not been empirically explored to a meaningful degree outside the US.



(Estimation, Continued from page 7)

While the functional form of market impact models is well agreed upon by researchers, the empirical estimation of the parameters has often lacked the boundary conditions which we find to be of critical importance. We present an information leakage rationale to justify the mechanism of our boundary conditions. Our market impact model for US stocks shows a very high degree of explanatory power.

We have also presented a mechanism by which the cost estimates of any market impact model can be extended from one data set to another, by using positive serial correlation as a proxy for illiquidity. The relationship between expected trade costs and positive serial correlation of returns across capitalization deciles of US stocks is shown to be almost exactly linear (R-squared over 90%). This should allow for at least reasonable estimation of market impact for those markets where databases of explicit trade data are insufficient or unavailable.

Finally, we present a means of estimating a market impact model using tick data. While computationally intensive, this method has the appeal that it be estimated without any attempt to identify the characteristics that differentiate liquidity across securities within a market. A great deal of computational effort and methodological refinement remains to be done on this approach.

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Technical Support Tip: Using the New BACKTEST Command in NisBatch2008

By James Williams

Ongoing enhancements to the lineup of Northfield's products and services include a recently added function to NisBatch2008. NisBatch2008 is Northfield's batch processing software and is a separate program from the Optimizer and requires an additional subscription. The program allows users to run optimization projects over multiple portfolios with different project constraints as well as time periods with a simple script. For more information about the NisBatch2008 program, please contact your Northfield technical support representative.

Presently, in order to run a backtest of a project over time, it is necessary to create a batch script using NisBatch2008 and to create a number of update files corresponding to the number of monthly periods under consideration. For a five year backtest, this would require an initial project file plus sixty update files. Each update file would contain information on the project's parameters to be changed for each month, such as risk model dates, security alphas, benchmark constituents, etc…

New BACKTEST Command:

The new NisBatch2008 backtest command greatly simplifies the setup of backtesting projects.

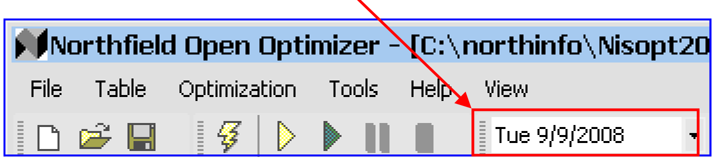
Instead of creating a lengthy script within NisBatch2008, a single line entry for the BACKTEST command is only required. The format of the BACKTEST command is:

BACKTEST <Date>

Where the <Date> format is: YYYY/MM/DD

BACKTEST Command Process

When using the BACKTEST command, NisBatch2008 will open the project file found in the batch script and will optimize the initial portfolio each month, from the backtest command date (BACKTEST YYYY/MM/DD) until the optimization date found in the project file. The location of the optimization date can be found in the Northfield Open Optimizer as seen below.

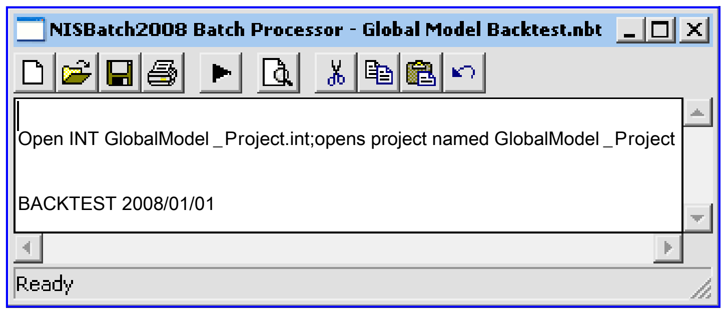


After each optimization, the optimal portfolio in Month$_{t-1}$ will be used as the initial portfolio for the next month, Month$_t$. This process will continue until the date specified in the optimization date field.

A quick way to try the BACKTEST command is to take a project file that uses Northfield's risk models (without any changes to the risk model name) and run the BACKTEST YYYY/MM/DD command using a date that is before the optimization date. The new NisBatch program will pick the appropriate risk model files for each month automatically.

BACKTEST Command Example:

NisBatch2008 script:



Backtest start date: 2008/01/01

Backtest finish date: 9/9/2008, from the optimization date in the NISOPT2008 project file GlobalModel_Project.int ***(see screenshot above)***

Backtest risk model dates used:
(2007/12/31, 2008/01/31, 2008/02/29, 2008/03/31, 2008/04/30, 2008/05/31, 2008/06/30, 2008/07/31, 2008/08/31)

Input files used in the project:

Portfolio file:	Initial Portfolo.csv
Benchmark file:	Benchmark<(YYYYMMDD)>.csv
Buy List file:	BuyList.csv
Alpha file:	Alpha<(YYYYMMDD)>.csv
Security min.:	Min Holdings<(YYYYMMDD)>.csv
Security max.:	Max Holdings.csv
Report File:	BacktestReport.csv

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Each of the output files will be created by adding the optimization date to the filename. In the project example below, a single output report “BacktestReportYYYYMMDD.csv” will be created for each month and will include information from the following reports: Optimization Summary, Analysis Summary, Risk Decomposition, Holdings Summary, Security Marginal Contribution.

The initial and optimal portfolio files will be saved each month in formatting consistent with Northfield’s Performance attribution tool allowing for a smooth transition to performance analysis for the backtest.

For the last optimization period, the reports are stored without the optimization date added to the filename.

Project File Using Excel Workbook for the Output Report

```
                 NISOPT: Project
                 Project Version = 2.01
               Optimizer Version = 1.30 (7.403)
              NISOPT: Risk Model
                            Type = Global
                      Identifier = SEDOL
                        Currency = USD
                            Date = 2008/08/07
                 Risk Model Path = ..\data
                     Factor File = i <(YYYYMMDD)>.mdl
                Correlation File = i <(YYYYMMDD)>.cor
                   Exposure File = i <(YYYYMMDDs)>.csv
                NISOPT: Holdings
                  Portfolio File = Initial Portfolio.csv
             Portfolio Weighting = Shares
         Default Portfolio Value = 300000000
                  Benchmark File = Benchmark<(YYYYMMDD)>.csv
      NISOPT: Security Selection
                   Buy List File = BuyList.csv
                      Alpha File = Alpha<(YYYYMMDD)>.csv
    NISOPT: Security Constraints
           Security Minimum File = Min Holdings<(YYYYMMDD)
 Default Security Maximum Weight = 7.000000%
           Security Maximum File = Max Holdings.csv
              Position Threshold = 0.250000%
          NISOPT: Industry/Sector/
  Sector Minimum Constraint Type = Relative to Benchmark
  Sector Maximum Constraint Type = Relative to Benchmark
        NISOPT: Transaction Cost
          Transaction Cost Units = Percent
  Default Transaction Cost (buy) = 0.300000%
 Default Transaction Cost (sell) = 0.300000%
              NISOPT: Round Lots
     Enable Rounding Adjustments = No
   NISOPT: Portfolio Constraints
        Maximum Number of Assets = 120
          Minimum Tracking Error = 0.000000%
          Maximum Tracking Error = 0.000000%
            NISOPT: Optimization
    Maximum Number of Iterations = 1000
                  Systematic RAP = 30
                Unsystematic RAP = 30
    Tracking Error Optimizations = 0
        NISOPT: Reports Settings
           Reports Settings Path = Reports
           NISOPT: Basic Reports
       Optimization Summary File = BacktestReport.CSV
           Analysis Summary File = BacktestReport.CSV
         Risk Decomposition File = BacktestReport.CSV
           Holdings Summary File = BacktestReport.CSV
  Security Marginal Contribution = BacktestReport.CSV
   Constraint Summary (Brief View) = No
       NISOPT: Portfolio Reports
          Initial Portfolio File = BacktestPortfolios.CSV
    Initial Portfolio File Units = Shares
          Optimal Portfolio File = BacktestPortfolios.CSV
    Optimal Portfolio File Units = Shares
```

Using Date Macros with Input files and Report files

For each interval period during the Backtest, NISOPT2008 reads the project file to determine which input file to use during that specific interval. For example, if the backtest period is three months, 2008/01/01 to 2008/04/01, the risk models used will be the periods 2007/12/31 to 2008/03/31. In addition, if there are input files in the project with names without date macros attached, such as price.csv or alphas.csv, NisBatch2008 will search for files with the date relevant to the interval, i.e. price20071231.csv or alphas20080229.csv. If a file with the appropriate date interval is not found, than the original file found in the project (price.csv, alphas.csv) will be used for each interval.

You can assign a date macro to any of the input files or report files such portfolio, benchmark, price, alpha, risk decomposition, optimization summary, etc…

If a date macro is not assigned to an input file than the system will use the same file for each monthly optimization. For example, a backtest project criteria calls for having a constant buy list for each monthly update and also security alphas that change each month, than in the project file the buy list file name should not have a date macro but the alpha file should.

Example: Buylist.csv, alphas<(YYYYMMDD)>.csv

There are two formats for the date macros:

1. **<(YYYYMMDD)>** Enclosing a date in parenthesis, (), in conjunction with using the greater than and less than symbols, <>, will result in the system selecting the risk model date.

Examples: ee<(YYYYMMDD)>.mdl, ee<(YYYYMMDD)>.cor, ee<(YYYYMMDD)>.csv will select the appropriate risk model dates (last day of month) for the Everything Everywhere risk model..

Benchmark File=northinfo\data\sp5_<(YYYYMMDD)>.hld will choose appropriate SP500 benchmark file from risk model directory.

2. **<YYYYMMDD>** Enclosing a date in just greater than and less than symbols, <>, will select the optimization date as specified in the project file.

Example: alphas<YYYYMMDD>.csv will select the alphas file corresponding to the optimization date.

It is recommended that parenthesis, ( ), should be used when using date macros with the risk model files. Input files created with date macro use either of the two date macro formats above.

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In addition, the date macro format can be in different combinations such as: <YYYYMMDD>, <YYYYMM>, <YYMM> <YYYY> <MM> or <MMDD>, etc…

YYYY: converts to 4-digit year: 2000, 2007, 2008, etc…

YY: converts to 2-digit year: 00, 98, 08 etc.

MM: converts to 2-digit month: 01, 02, 03….12

DD: converts to day of the month: 01, 02, 03, etc…

Though you may use the date macro with the risk model files, it is not necessary to do so, since the NisBatch2008 program recognizes which risk model dates and which currency to use from the project file.

Optimization date (format <YYYYMMDD>) and risk model date (format <(YYYYMMDD)> are different. For example:

OPEN APT apt1.apt
(located in:\northinfo\Nisopt2008\Samples2008\apt\)

BACKTEST 2005/01/05

If your file apt1.apt has optimization date 2006/01/01, then dates in format <YYYYMMDD> will be: 2005/01/05, 2005/02/05, 2005/03/05 … 2006/01/01 – i.e. optimizer will increment month up to the last date in apt1.apt

Dates in format <(YYYYMMDD)> will be: 2004/12/31, 2005/01/30, … 2005/12/31 – i.e. date of risk model file for selected month. Please note that the first risk model used will be from December, 2004 not January 2005.

Tips when using the BACKTEST command

Choose “Shares” as the portfolio weighting for the portfolio holdings file used in the project as well as for the initial and optimal portfolios in the Reports - Portfolio section of the project. “Percent” weighting will give correct percent values for initial and optimal portfolios during the backtest process but erroneous share values.

It is recommended to use date macros with input filenames that will have different values each month (specifically benchmark, alpha files), and any constraints that change month-to-month such as composites or attributes.

For further inquiries, contact Technical Support in Boston: support@northinfo.com or call 617.208.2080. European clients can contact: george@northinfo-europe.com or call +44-(0)-20-7801-6260. In Asia, contact James Williams, james@northinfo.com.

Northfield Staff Speaking Engagements

Northfield’s Nick Wade presented “Balancing Technological Change with Intuition" at the Macquarie Global Quant Conference in Singapore on August 8th.

On August 19th, Northfield President Dan diBartolomeo spoke on global liquidity and trading costs at the Boston QWAFAFEW meeting. On September 8th, Dan gave the same presentation at the London Quant. Group Annual Conference at Cambridge University in England. Dan will also be presenting on this same topic on November 19th in at the TradeTech Asia Summit in Singapore.

On September 26th, Dan will be speaking about hedge fund risk assessment at the FRA Hedge Fund Conference in New York City.

On October 30th, Dan will be presenting at the "How I Became A Quant?" program at MIT, organized by the International Association of Financial Engineers. For further details, visit http://www.iafe.org/10302008.html

On November 6th, Dan will be speaking on optimization techniques at the FactSet Investment Symposium in Orlando, Florida. Visit the Factset website for further details, http://www.factset.com/events/ussymposium2008.

If you have any suggestions of what you would like to see covered in upcoming issues, please e-mail your ideas to staff@northinfo.com

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