

Portfolio Strategy

North America

Market Commentary

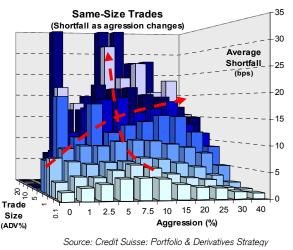
22 July 2009

Phil Mackintosh + 1 212 325 5263 Laurent Boldrini +44 20 7888 2041

Key points

- Our online EDGE tool now includes a beta version of our new pre-trade model. This is a semi-empirical model that estimates impact cost & execution risk.
- We have calibrated this leveraging Credit Suisse's extensive post trades database (ExPRT).
- > The main improvements in our model are:
 - Better, broader, global data
 - Simple portfolio management
 - A 3D impact model where aggression as well as trade size affect impact cost
 - Separation of risk and cost, to give traders more control over their level of risk aversion.
- This report shows how we have calibrated our real-world trade results into a theoretical model, and details the inner workings of our impact model.
- More information on how (and where) to use our new model is included in this report: <u>EDGE Update: **NEW</u> <u>Portfolio Tools**</u>

Exhibit 1: Observed Impact Cost Surface



Trade Strategy

A New EDGE in Impact Cost

Our new Impact Model (Now in EDGE)

We have included a beta version of our new Pre-Trade model in our new EDGE > Portfolio suite. The model we have adopted builds on much that has been learned in earlier reports:

- Estimating Execution Costs, where we analysed the dynamics of shortfall across duration and aggression, and
- Evolution of Impact Cost Models, where we discussed popular impact model mathematics, and the key weaknesses of each.

Consistent with the evolution of impact models, our new pre-trade model is based off the Almgren & Chriss models. We calibrated the model using real execution data, into an underlying theoretical model - in this sense this is a semi-empirical model.

Enhanced Portfolio Tools

We have built a beta version of the new impact model in EDGE, which will offer a number of benefits to users:

- Better global data capture and breadth (now over 47,000 stocks).
- All analytics are now available in one place:- in <u>EDGE</u>. This saves time as portfolios will only need to be loaded once. In fact, clients working live portfolio trades with CS can automatically push each trade-list into EDGE's portfolio analytics suite.
- The EDGE portfolio analytics suite includes: pretrade tools, positions, performance and risk calculators, our event calendar, as well as online market guides & settlement calculator.
- More information on how (and where) to use our new model is included in this report: <u>EDGE Update: **NEW Portfolio Tools**</u>

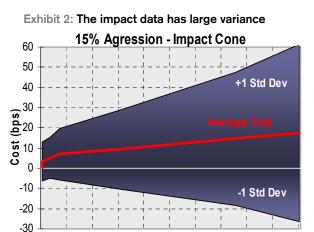
Impact Surface

We think a key improvement in the EDGE impact model is the introduction of a 3-dimensional 'cost surface'. This captures a feature we observed in real execution data – where execution style (aggression) as well as trade size both affects the cost of executing an order (see Exhibit 1).

Separation of Execution Cost & Risk

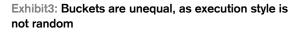
As we highlighted in **Evolution of Impact Cost Models**, one of the issues with Almgren & Chriss models is the interpretation of their 'risk aversion' function - especially setting an appropriate λ in their formula. We also propose that the addition of risk & costs is often not optimal. The beta version of our model separates these terms completely, to allow users to see how different aggression levels affect cost and risk components. Initially, this should give traders more information, and control, of their trading trade-off.







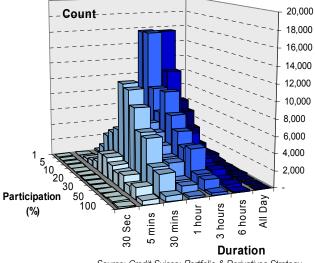
90 100



40 50 60 70 80

0

10 20 30



Modeling the Data Set

In our earlier report Estimating Execution Costs, we also highlighted some important dynamics of the data available to us at Credit Suisse.

A benefit of our data over publicly available datasets is that we know the parent order size and the side for each order. Many academic studies lack reliable classification of individual trades as buyer- or seller-initiated, or information about parent level total order size.

However, we acknowledge that we lack information of on very large orders as generally Credit-Suisse would see only slices of these executions by traders. Additionally, we lack reliable information about opportunity costs, as our 'start time' is the time the order is received into CS systems, and we generally can't see the overall average cost of multi-day orders.

Persistent strategies for Better Results

We also excluded non-systematic orders with high opportunity costs - like MOC orders, limit orders and stealth execution strategies, (Guerilla, Sniper). Consequently, our data reflects performance of time and participation sensitive strategies: Volume-in-Line, TWAP, and VWAP.

Because we are dealing in averages, we have also windsorized our data. This removes radical outliers that affect conclusions we can draw from averages.

A lot Of Data

We first fit our model to a dataset with a very high number of samples for global data. This Global function is then used as an a priori surface shape to calibrate per exchange and market cap group. (And also to update over time as more post-trade data becomes available).

The a priori surface for our model uses 3 years of post-trade data, after filtering ~260,000 trades in our data set, c.f. Almgren et al. 2005 ~29,000 trades after filtering. Importantly, our data set is from prior to the extreme market volatility seen in 2008 & 2009.

Statistical Uncertainty

There is also a high degree of variance in our dataset (see Exhibit 2). Consequently, we need the high quantity of data to get meaningful results.

Even with such a large sample size, we still found that trade data was concentrated into specific buckets (exhibit 3). We found a concentration of:

- INLINE orders at around 20% aggression.
- VWAP orders lasting most of the day (as fairly passive execution rates)

To ensure most buckets had reasonable statistical properties, our buckets are quasi-log spaced - but even with this modification, some we have an uneven sampling distribution, buckets lack a reliable quantity of data given the variance of each bucket.

Curve Selection & Fitting

We choose a power-law modified logistic function, which can take a similar shape as the functional form assumed in previous studies. Our function choice is justified by our central hypothesis: "Liquidity begets liquidity".

The Edge pre-trade model is structured to reflect stylised empirical facts via the detailed calibration of an underlying theoretical model. In this sense this is a semi-empirical model.

Source: Credit Suisse: Portfolio & Derivatives Strategy



Participation & Duration

We saw in Exhibit 1 that both trade size and aggression affect an execution cost. Consequently, our model is built as a 3-D surface to reflect this.

But we have rewritten the equation in terms of participation and duration – knowing that:

Normalized Trade Size = Participation x Duration.

Consequently, the key variables in the equation are:

- P = Participation = target aggression level (Order Size / Expected Market Volume over the Duration of the Trade).
- **D** = Duration, is the time of the trade. Duration is usually expressed in days.

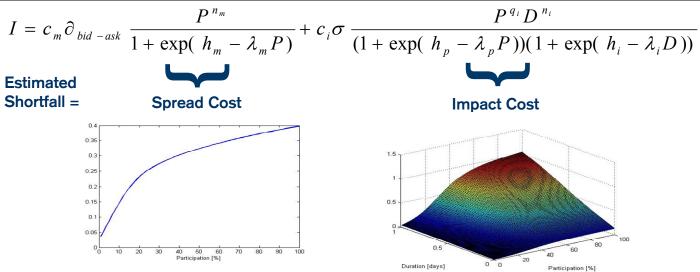
An Overview of our New Model

Our new model breaks cost down into 2 cost components and a supplementary 'execution risk' component:

COST = Spread + Impact

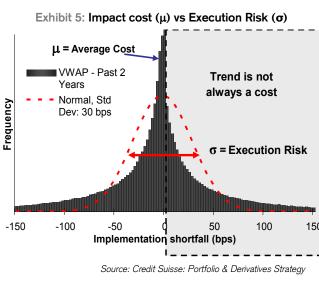
- Spread: a dynamic function that increases with aggression. In essence it represents the expected % of orders expected to cross the mid-touch spread. Because of the unavoidable nature of spread costs, it is sometimes referred to in studies as 'Mechanical' cost.
- Impact: Represents the amount an order moves the average price through the far-touch. This is affected by trade size and aggression. Because it provides signals to the market of your ongoing activity, it sometimes referred to in studies as 'information cost'

Exhibit 4: Mathematical expression of the market impact model



Where c_m , n_m , h_m , l_m , c_i , q_i , n_i , h_p , l_p , h_i , and l_i are the configurable model coefficient parameters.

Source: Credit Suisse Portfolio Strategy



Execution RISK - is not always a cost

As detailed in our earlier report **Estimating Execution Costs**, any expected cost estimate has a relatively low degree of accuracy – thanks to trend and other systemic factors that occur during an execution. This could be considered the execution risk. Our model shows the expected variability around our estimate, at a portfolio level.

Everyone has different Alpha!

We also concluded that the volume and delta neutrality of our execution data resulted, for practical purposes, in an informationless trade. That being the case, the market impact function (spread + impact) should be considered the expected shortfall 'before alpha'.

We saw in **Evolution of Impact Cost Models** that some alpha signals decay much faster than others – and may include significant delay costs. We also realize that each investor's alpha is different (in value, confidence & decay).

For this reason, customized alpha & decay measures would be better for trade scheduling than risk aversion based on stock volatility. However this adds complexity to the Pretrade - consequently, the Beta version of our impact model currently in EDGE does not include any alpha cost.



Spread Costs

Spreads are the most obvious, and immediately unavoidable, cost of starting an order. They are also affected by aggression levels, local dynamics, and intraday trade timing. How we model for this is discussed below.

More Aggression = More Spread Costs

It is generally assumed that a more passive execution will capture more of the spread, while aggressive orders will need to pay the spread away more often.

We also see this in our calibrations for very short duration executions. We know that very short duration orders (average duration around 30 seconds) that trades are very small and incur little trend costs. As we see in Exhibit 6, on average:

- Very passive orders get completed, close to mid-spread.
- Less than 20% aggression, the order gets completed, within the spread.
- As aggression increases, the percentage of the mid-spread crossed increases at a decreasing rate.

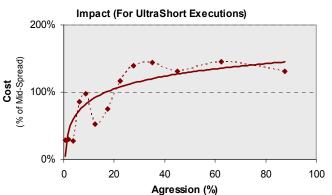
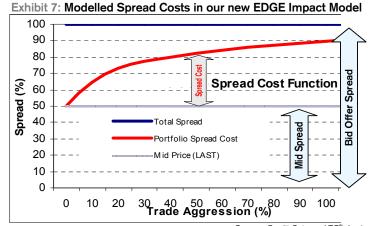


Exhibit 6: Actual Average Impact vs Spread (by aggression)



Source: Credit Suisse: AES® Analysis

It's important to model spread costs separately

Our previous analysis has shown that spreads vary significantly depending on factors such as:

- average stock prices
- regulations by country & market
- liquidity and market cap
- the volatility environment

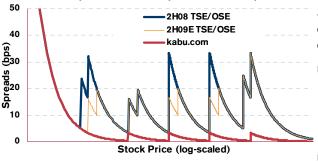
We summarise these impacts below.

Our key conclusion from this analysis is that spreads are dynamic, and they are influenced significantly by stock & country specific factors.

Capturing live spreads, by stock, should address the stock & country specific issues of including accurate spread costs in our model



Exhibit 8: Japanese Market spread costs (vs price)



Source: Credit Suisse: Portfolio & Derivatives Strategy



Spreads Change by Region & Cap Range

Spreads (and therefore spread costs) vary significantly across the globe (see exhibit 10). Specifically, many countries in non-Japan-Asia (NJA) have especially wide spreads. This is caused by a combination of:

Some Regulators in Asia fix spreads at levels greater than 1 cent (see exhibit 8). More details on country spreads can be found by country <u>here</u>, and in our <u>Global Markets Handbook</u>. For information on Asia specifically, see: <u>Asia Pacific Equity Markets Handbook - The Whole Enchilada</u>, <u>The New Normal in Asia</u>

Average stock prices are much lower in some countries than others. In these countries, 1 cent spreads represent a higher percentage cost (see exhibit 9).

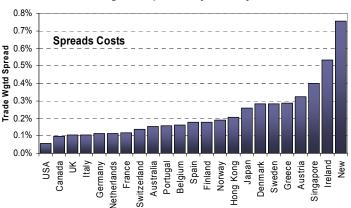


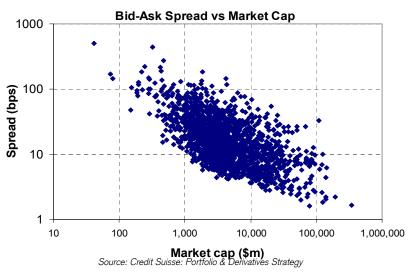
Exhibit 10: Trade Weighted Spreads by Country)

Source: Credit Suisse: AES® Analysis

Spreads Vary across stocks - Liquidity & Market Cap

We also find a relationship between large and small cap stocks – and their spreads – that persists at each point in time (Exhibit 11). Generally, larger cap stocks trade with tighter spreads. While the smallest cap stocks seems to trade at the widest spreads.



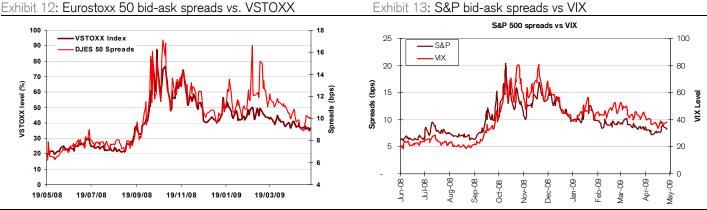




Spreads Change over Time - a lot

During the recent market crisis, we have noted spreads have increased across the board as volatility increased (see: <u>As The Dust Settles: Analyzing Microstructure Changes</u> & <u>After one year of MiFID</u>).

For example: Spreads for US & European large cap roughly doubled toward the end of 2008, and European blue ships are now trading with spreads of around 12bps compared to only 7.5bps in July 2008, a 60% increase. We observed an even bigger (3 fold) increase in US small cap stocks during the same period.



Source: Credit Suisse Portfolio Strategy

X Exponential time-weighting of live spread

data means spreads in EDGE have a half life

just over 2 hours. This should mean spreads

change fast enough to be representative of

the current day - without exaggerating the

impact of short term spikes that would not

persist for the life of larger trades.

Source: Credit Suisse Portfolio Strategy

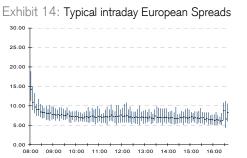
Spreads change Intraday – a little (usually!)

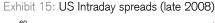
However we find that spreads change far less intraday. Typically, spreads are slightly higher in the morning, while price discovery and gap risk occurs. Then, as trading settles down, the spreads typically normalize.

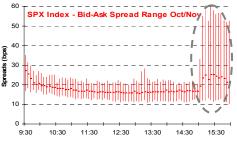
However, during the recent crisis, we observed some unusual intraday spread patterns. Not only did spreads increase throughout the day, we observed:

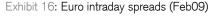
- As the VIX peaked in the 80's, we saw US spreads increase significantly in the last hour of trading – and noted that the largest spreads blew out to over 50bps during that period (Exhibit 15).
- In February 2009, in the heart of the most recent aggressive selloff, European spreads were far less stable around the US open and into the European close than normal (Exhibit 16).

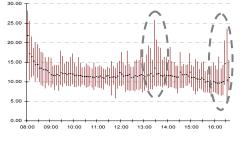
In particular, trading into the close just before the auction has become a lot more risky as it seems that some traders are willing to complete execution at any cost in order to avoid overnight gap risk, while apparently statistical arbitrage automats now stop trading well before the close, making it more difficult to find matching liquidity.











Source: Credit Suisse Portfolio Strategy



Showing Spread Costs in EDGE

Our calibration of Impact for the new model in EDGE attempts to capture these phenomenon. As detailed in exhibit 1, the spread component of our model is an exponential function that increases the spread cost as aggression rises. The EDGE impact cost model:

- Assumes that even the most passive order will only capture 50% of the spread, by all marking portfolios to 'mid' prices
- Increases the percentage of spread crossed as aggression increases (red line), using an exponential function similar to that observed in exhibit 7.
- Calibration found that even high participations can sometimes occur on the near-touch. Consequently, the spread function reaches a maximum at 90% of the spread being crossed.

In the website (more info on using EDGE at the end of this report):

 Wtd Bid-ask spread: represents the full spread (bid – ask), averaged for all stocks in the basket based on each stocks trade weight.

The Pretrade also includes a chart showing how much of the portfolio (by weight) falls into a increasingly larger spread buckets. This will show whether spread costs are high just for a few small stocks, or for some of the largest stocks in the list.

Portfolio Spread Cost: represents the actual cost of crossing the spread for the trade, based on your level of aggression. (Because it is measured from Mid – it will always be significantly less than the total bid-ask spread

A Weighted Spread Calculation in EDGE

Pre-trade planning is most useful for larger trades. Consequently, our spread capture model is geared toward most accurately reflecting the spread costs of a reasonable sized trade – being one that is expected to execute over hours to maybe a full day.

To reflect this, our EDGE spread model will:

 Capture live spreads for each stock around the world: Data is captured for each stock from around the world, every 10 minutes (during live markets, except at open & close).

This ensures that our spreads are stock -specific, regardless of country or market cap factors, or whether markets are closed. Our expanded universe covers over 40,000 stocks.

- Average the data to better reflect the spreads seen over the life of a larger trade:
 - We then exponentially weight the data, so more recent spreads contribute more to the average. This rate of decay is most representative of a 2-3 hour trade.
 - Almost 2/3rds of the spread comes from the most recent 3 hours of data – but over 12% of the spread relates to data more than 1 day old.
 - This means that pretrades are not overly sensitive to the time of day that they are run (as intraday live models are subject to be), or very short term spikes in spreads (which historically don't usually persist).

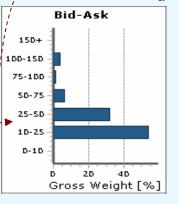


Portfolio Summary	Buys	Sell	Total
Value [USD]	142.3m	129.3m	271.6m
Shares	8,515,838	6,237,830	14,753,668
Names	24	15	39
Liquidity [%]	20.14	10.55	15.58
Max Duration	6.25	2.76	6.25
Wtd Ave Duration	0.81	0.42	0.62
🕶 Wtd Bid-ask [bps]	17.45	9.19	13.51
Impact Summary			Total
Portfolio Spread Cost (bps,	. from mid)		3.45

Portfolio Market Impact (bps)

Portfolio Impact Cost (bps)

Source: Credit Suisse: Portfolio & Derivatives Strategy



45.94

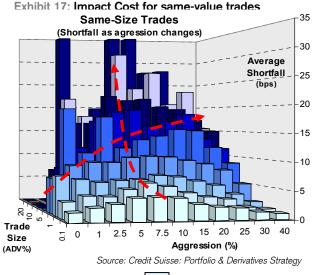
49.39



Source: Credit Suisse: Portfolio & Derivatives Strategy

Exhibit 1: Contribution of data to bid-ask spread





Impact Costs

Scaling the Post-Trade Data for Model Fitting

As we detailed in our earlier report, **Estimating Execution Costs**, we collected real executions from almost 300,000 trades from our ExPRT system over a 2 year period.

Bucketing real executions by trade-size and aggression (exhibit 17), we found that cost increased a lot as trade size increased, and a little as aggression increased. Viewed in this way (size + aggression) we create a 3-dimensional execution surface, rather than a 2-dimensional execution curve.

We have used these results to calibrate our EDGE impact model.

A 3-D experience!

As we detailed in **Evolution of Impact Cost Models**, while all impact cost models capture the fact that larger trades cost more – most do not show the increased costs caused by higher levels of increasing aggression.

This is particularly significant for investors using an Almgren & Chriss style semi-empirical model. One of the important benefits of these models is the optimization of aggression levels to minimize cost + risk (adjusted for risk aversion).

However, as we see from real results, increasing risk aversion (aggression) itself adds to costs for the same sized order. Our execution surface is calibrated in 3 dimensions to account for this.

Our model is actually a function of participation & duration (see exhibit 18). But as **Trade Size (in ADV) = Participation x Duration,** converting from Exhibit 17 to exhibit 18 is a relatively simple process.

Our total estimated shortfall calculation is initially calibrated over this new surface, resulting in a smoother modelled function (Exhibit 19).

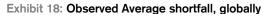
The Model 'S'hape

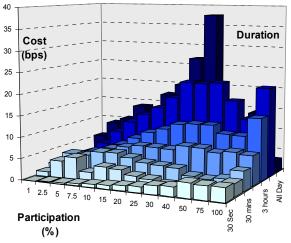
Impact cost is often modelled as a power-law, scaled usually by normalized trade size. We found the most descriptive model used power-law modified logistic function, commonly used to model population growth. A feature of these models is an 'S' shaped curve.

This curve retains a (largely) similar shape as used in other models – Costs increase at a decreasing rate as order size increases. However this curve has 2 distinct benefits:

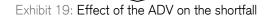
Intuitively, the S curve represents 'signalling' risks, as an order moves from 'too small to detect' to 'large enough to cause impact'. The initial 'S' shaped part of the curve (marginally increasing costs) occurs for very patient orders. Then as an order increases, we see decreasing marginal costs – which represents the attraction of additional liquidity because of the price move already caused by a trade. Our model shows that this is more significant for longer duration orders, where order submission (and thus signalling) becomes persistent.

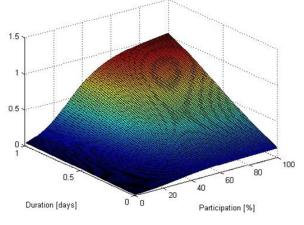
 This curve tends to be limited at extreme levels, rather than increasing indefinitely. Examples of extreme limits are common in the stock market – such as pricing large secondary offerings or acquisitions, both of which are valued assuming significant instantaneous liquidity ('overnight')











Source: Credit Suisse Portfolio Strategy



Portfolio Strategy

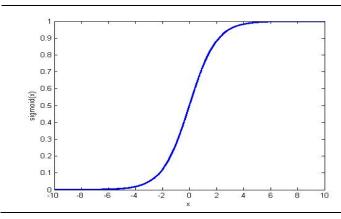
$$Logistic(t) = \frac{1 + m \exp\left(-\frac{t}{\tau}\right)}{1 + n \exp\left(-\frac{t}{\tau}\right)}$$

Examining the Logistic Function

A logistic function is a generic S-curve, generally used to model growth of some set over time t:

Exhibit 20: Formula & Shape of Mathematical functions used

$$sigmoid(t) = \frac{1}{1 + \exp(-t)}$$



4.5 4.5 4.5 3.5 3.5 2.5 2.5 2.5 1.5 1.5 0.5 0 0 2.4 6 8 10 12 14 15 1820

 $f(x) = \frac{x}{1 + \exp(h - \lambda x)}$

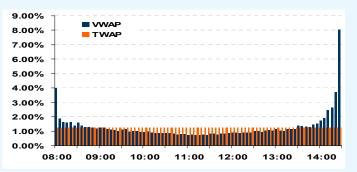
EDGE Assumes TWAP-type Curve

Duration is critical to our impact calculation, and also to trade scheduling. This causes a modeling problem:

- Volume typically occurs in a 'smile' throughout the trading day (see chart below). This means there is more liquidity around open and close. Consequently, an execution in-line with volume should actually have longer maximum duration in the middle of the day, than at other start times.
- BUT, our calibration is independent of start times. Because of this, it's not possible to know whether a more liquid period costs less to trade (as our formula would suggest) or whether this just reduces duration & therefore execution risk.

In EDGE, we do <u>not</u> use intraday volume curves. Although this leads to mis-estimation of duration for PreTrades run during live markets – it will give more consistent and realistic shortfall estimations – independent of the time-of-day that a report is run.

This more generalized result also makes sense for a global PreTrade calculation – as it does not matter how long until closed markets re-open when determining duration or impact.



Source: Credit Suisse Portfolio Strategy

Logistic Growth Functions in the Stock Market

Logistic functions are commonly used to model population growth. As such, they initially grow at an increasing rate. In an impact cost model, we equate to signalling costs, which affect an order as soon as it becomes large enough to overwhelm the far-touch volumes and/or be detectable because of its persistence.

As populations grow into their environments, resources become relatively scarce, slowing additional growth rates. We see this in all impact cost models, where larger market moves attract more liquidity providers, causing costs to increase at a decreasing rate.

Participation & Duration Trade Size (in ADV) = Participation x Duration.

The key variables in our equation are:

- **P** = Participation (also referred to as aggression): represented as the Order Size / Expected Market Volume over the Duration of the Trade. Note that Participation will only be the same as % of ADV when an order takes exactly 1 day to trade. Participation is expressed as a percentage and, in theory, is limited to a range 0-100%.
- **D** = Duration, is the time of the trade. Duration is usually expressed in days. The way we use and compute the duration assumes a TWAP curve as we never know at what time of the day an order is going to be executed and as it is the most neutral way to estimate an average execution.

From linear regression results, participation and duration appears to be good candidates for model parameters. However, they are not completely orthogonal.



Custom Fitting the Global Model to Single Stocks

Previous studies, e.g. Lillo, Farmer and Mantegna (2003) found impact cost had dependence on total market capitalization as well as trade factors. We account for this by down-sampling our data-set by exchange and market cap bins and then fit our coefficients for each group, effectively tailoring the model to each exchange and market cap range.

The global (parent) data-set is fit using a non-linear least squares approach to find the coefficients of the model, using an *a priori* with large uncertainty

After fitting the global surface, the resultant coefficients are then used in turn as the *a priori* value in a non-linear least squares/Levenberg-Marquardt approach to find fit the surface for the exchange and market cap binned data. (This approach can be extended as we record more trade data which we want to incorporate to our model fit, using the current coefficients as the a priori value per exchange and market cap group).

Levenberg-Marquardt Algorithm

The Levenberg–Marquardt algorithm (LMA) provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least square curve fitting and nonlinear programming.

The LMA interpolates between the Gauss-Newton Algorithm and the method of gradient descent. In many cases the LMA finds a solution even if it starts very far off the final minimum.

Parameters selection

As we are building an empirical model we are fundamentally limited to measurable parameters recorded historically in our post-trade analysis and any additional market or stock specific data that can be temporally mapped over the duration of the trade.

We reduce the dimensionality of the problem by focusing on several key factors: Market Volume, Participation, Duration of the trade, the Bid-Ask spread of the stock, and the stock volatility. The stock can be further characterized by its Market Capitalization and its Parent Exchange.

To fit the global model better at the single stock level, we tested the descriptive power of a number of stock specific variables, including:

- Liquidity: It was most critical to normalize for liquidity (hence measuring Trade Size in ADV).
- Volatility: Stock level volatility was important descriptor of impact especially for more volatile stocks
- **Country**: the country is not a parameter in our model but we take it into account when we specify the global surface for a specific country.
- **Spreads**: Spreads are stock & country specific and particularly affected by aggression levels, as we detailed above.

Key Assumption: Trend Costs = 0

On any given day, market impact (or shortfall) depends on many factors, including market sentiment (trend), macro-economic data announcements around the time, stock-specific news, etc.

However, by inclusive sampling of 2 sided trade data over 3 years, we feel our average shortfall, and therefore our impact cost estimates, are largely 'trend free'. Effectively, the trend component averages close to zero.

 $\Sigma(\varepsilon) = 0$

Instead, trend costs in our model will be seen via the 'execution risk' component – as they affect the how different each shortfall observation is to the longer term average.

Interestingly, we can also analyze Trend costs as calculated using our ExPRT methodology (See Ex 22). This shows that trend costs are in fact very close to zero in most markets – both versus the average shortfall, and especially as a percentage of execution risks

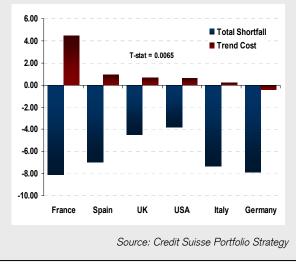
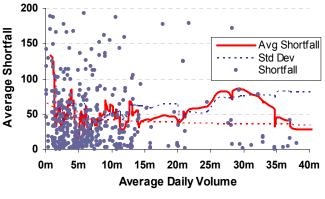


Exhibit 22: Actual Trend cost are ~ Zero



Exhibit 23: Average shortfall for same shares-to-trade



Source: Credit Suisse Portfolio Strategy

Normalizing for Liquidity

Trade size (in shares or \$) is not useful in determining expected shortfall:

- Observed impact varies significantly using consistent 'shares-traded' totals, as we do in Exhibit 23 (note that the standard deviation in this exhibit is generally wider than the average impact).
- Structural differences across markets, such as different average share prices (exhibit 9), make raw 'shares-to-trade' a meaningless value.
- Large companies naturally trade with higher \$ turnover.

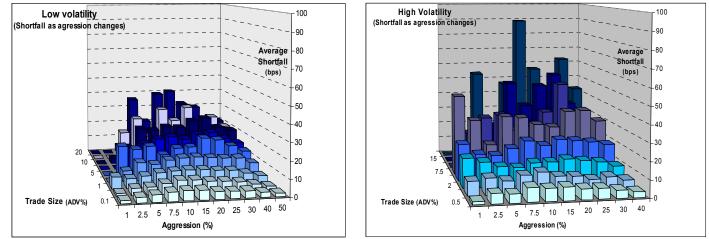
We found it was most important to normalize for liquidity. This simply means converting trade size into a measure of ADV. For example, the following two orders should have roughly the same impact, as both have a trade size of 0.5:

- 50,000 shares of a 100,000 share/day name = 0.5 ADV
- 5m shares in a 10m share/day name = 0.5 ADV

Stock Volatility

Bucketing executions by volatility, we found significant differences between the costs of trading high-volatility stocks, versus most other stocks. This is consistent with many other studies. Consequently, we include realized stock volatility as a scalar in the impact calculation

Exhibit 24: More volatile stocks have higher average shortfall for the same sized order



Source: Credit Suisse Portfolio Strategy

Does the EDGE PreTrade include Volatility?

The formula on page 3 shows stock volatility (σ) is a factor in our cost model. Note that it is:

- Calculated based on 90 historic prices.
- Exponentially weighted so that recent volatility contributes more than older returns consistent with GARCH-style volatility models.
- Included as a linear factor, independent of market volatility (see below).

Stock volatility is also a key factor in the risk component.

How does this compare to real results?

Real execution results actually indicated that volatility was a nonlinear factor for impact (materially increasing impact for high-vol names only). We also saw that it was mostly a 'relative' factor (See exhibit 15 in <u>Evolution of Impact Cost Models</u>, market-wide vol increases did not result in higher single stock slippage).

However, we expect this should have a minimal impact on most PreTrades, as: Market volatility has since mostly normalized, and the model calibration period excluded the recent vol spike. Over most portfolios, the non-linearity should be diversified away.



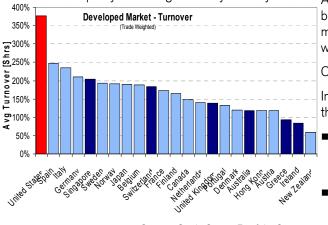


Exhibit 25: Liquidity & Trading Varies by Country

Source: Credit Suisse Portfolio Strategy

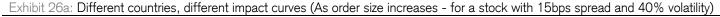
Country Specific Curves

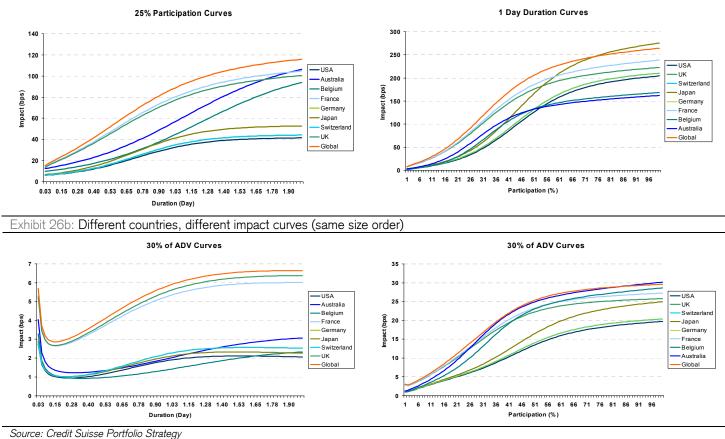
After adjusting for liquidity & volatility, we still found significant differences between the cost curves across countries. This is most likely due to unique microstructure, trading rules and participants in each stock market around the world, also evident from global liquidity characteristics (see ex. 25).

Consequently, we have customized our impact calibrations by country too.

In Exhibit 26, we show slices across each 2D axis of our surface. Overall, this shows that:

- Larger developed markets are generally cheaper to trade than the global average with US, Switzerland & Japan among the cheapest as orders get larger.
- Markets with lower liquidity, like Australia & Belgium, seem to be able to absorb very high participation levels with less impact than broader and more liquid markets – although these markets are also among the most sensitive to increasing aggression levels for a same-sized order.
- For large orders, extending the duration affects performance in UK and France more than other major markets – which may indicate signalling, is a greater risk in those markets.







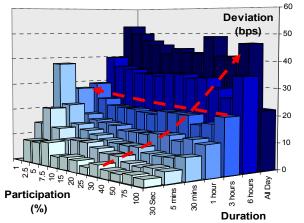
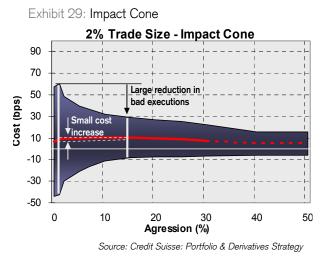


Exhibit 27: Standard Error (by aggression and time)

Source: Credit Suisse: Portfolio & Derivatives Strategy



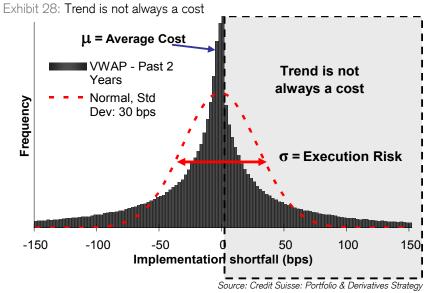
Execution Risk

Variance of Implementation Shortfall

When we plot the standard deviations of each bucket (around their averages) we see that in most points, the average shortfall is small relative to the variance. We also see that this variance increases with duration (Exhibit 27).

Intuitively, the longer the trade lasts, the more time trend risk and other stock specific news has to influence a stock, and hence the more the actual trade result varies from average. We also see this in real executions (Exhibit 29).

We call this the execution risk – as it represents the standard amount that executions miss our estimates. However is important to highlight that there is roughly an equal chance that trend results in a better or worse result (for a no-information trade).



Risk is influenced by Trend (Trend Risk?).

The blue zones in exhibit 30 & 31 show the estimated execution risk being 1 standard deviation around the average shortfall (red line).

- Exhibit 32 shows that execution risk seems almost linear with duration,
- Exhibit 27 shows it is independent of aggression.
- Exhibit 29 shows the trade-off between risk & cost, for the same trade

Exhibit 31: Error seems independent of aggression

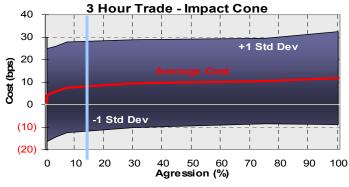
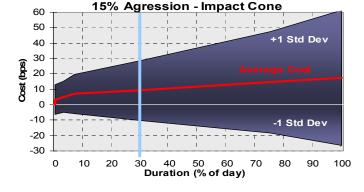


Exhibit 30: Error is almost linear with Duration



Source: Credit Suisse: Portfolio & Derivatives Strategy



Single Stock Execution Risk

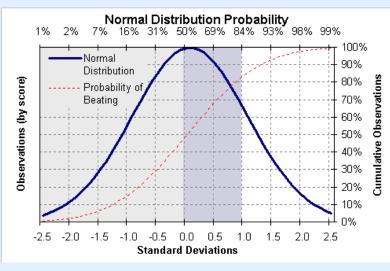
INTERPRETING COST + RISK IN EDGE

In contrast to Almgren et al (2005), we resist the temptation to add risk directly to cost – although users comfortable with the λ function in Almgren's model can do so themselves with simple algebra. (See **Evolution of Impact Cost Models**)

In our new PreTrade in EDGE (see appendix), we show cost and risk separately. The "risk" term is equivalent to ± 1 standard deviation, dependent on the stock, and the duration of the selected execution strategy. It's a measure of how much executions diverge around the average (risk), not a cost per-se (see Exhibit 29, blue area = risk, red line = cost). In the summary, it is also portfolio adjusted (see next page).

We also show a total for COST + RISK. Interpreting this is all about probability. Statistically: you should expect to <u>beat</u> the <u>Cost + Risk</u> level more than <u>83% of the time</u>. (see example below).

Execution Risk is Probability 101



- **\blacksquare** $\frac{2}{3}$ rds of observations fall within ± 1 standard deviation
- Therefore, $\frac{1}{3}$ of observations fall outside ± 1 standard deviation
- Which means 17% (1/3 /2) fall on each side
- Which means 83% (100% 17%) of the time you should beat COST + RISK

That's not Normal!

** note: all these statistics work for a normal distribution. Unfortunately, the actual distribution is far from normal (see Exhibit 28, it's got a pointy middle, with fat tails). This would actually result in more than 83% of executions beating the Cost + Risk level. However, the fat tails mean that those executions that 'miss', will have a much more significant impact on P&L than forecast too

As we saw above, execution risk is largely a function of time and volatility; and we consider it analogous with 'trend risk'.

Almgren et al (2005) used a similar concept when building their model based on trade rate – where they include a risk term based on **stock volatility x** $\sqrt{\text{time}}$ to approximate the execution risk. (See <u>Evolution of</u> <u>Impact Cost Models</u>, and grey box below)

Consequently we follow Almgren's approach, and model risk based on the each stocks volatility, and the time it is exposed to market factors. But importantly:

- Reducing aggression will increase the duration of an order – as will extending the duration of a VWAP strategy
- Increasing duration increases the time that trend (and news) has to influence the stocks price
- And consequently, risk will increase as duration increases

There is a significant similarity between our execution risk term, and old Inventory Risk costing models, as we show below.

COMPARISON OF 2 MODEL FORMULAE

Inventory Cost

Recall from <u>Evolution of Impact Cost Models</u> that the formula for inventory cost is:

$Cost = k x \sigma x \sqrt{(time)}$

Execution Risk

In our model, this concept, and therefore the formula, is adapted for the execution risk.

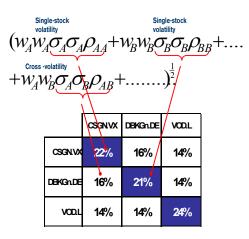
$$\mathsf{Risk} = \mathsf{P}_{\mathsf{o}} \ge \mathbf{\sigma} \ge \sqrt{(\mathsf{D} / 3)}.$$

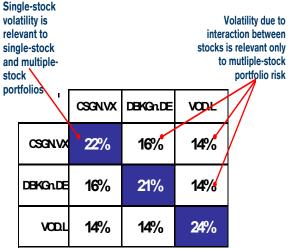
Where:

- P_o the initial notional position and
- D the duration of the trade
- √(D/3) represents the time weighted exposures.. As the day progresses, executions shrink residuals, thereby reducing risk, according to this formula P_t = P_o x (1 - t / D). This represents the integral of the open positions throughout time.

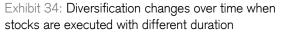


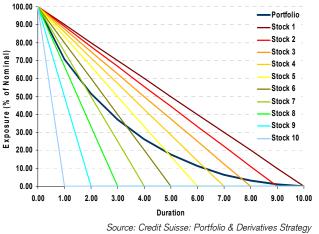
Exhibit 33: Calculating the Portfolio Risk





Source: Credit Suisse Portfolio Strategy





Portfolio PreTrades

The current EDGE model has been calibrated uses hundreds of thousands of orders – scaled for inputs including bid/ask spread, volatility, duration, relative trade-size and market participation rate. Consequently the model is highly calibrated on a single stock level.

Factoring the impact at a portfolio level is a more complex problem. We know that cross-correlations should reduce risk, and long-short portfolios could even see reduced impact versus one-sided trades.

The Edge pre-trade model is completely transferable from single-stock portfolios to multiple-stock portfolios. In the beta version of PreTrade, now in EDGE, we have doe the following to adapt our portfolio level results:

- Impact: is a simple weighted sum of the direct impact. In time, we will calibrate this properly based on real portfolio executions from our Program Trading desk.
- **Execution risk:** is scaled to include cross correlations across the portfolio, weighted incrementally for the remaining residuals over time.

to Portfolio Risk – the Diversification & Residual Effects

The Portfolio risk term takes 2 key factors into account:

1. Diversification

Recall from Modern Portfolio theory, that correlations & diversification reduce the risk of a portfolio below the risk of the individual stocks, as shown by the formula below..

Portfolio variance:
$$\sigma_p^2 = w_A^2 \sigma_A^2 + w_B^2 \sigma_B^2 + 2 w_A w_B \sigma_A \sigma_B
ho_{AB}$$

We adapt this approach to calculate portfolio execution risk, as we show in Exhibit 33.

Intuitively, 2-sided portfolios have less 'execution risk' as trend affects on long positons should be mostly offset by short positions. This will also occurin our model, as offsetting positons in 2-sided portfolios will more likely have negatively correlated returns – thus increasing the correlation benefits in the risk calculation.

2. Dynamic Residuals

For portfolio risk calculations weights are constant. However in a tradelist, executions result in positons that change all the time. Because of this, the remaining execution risk actually shrinks throughout the day.

Additionally, some execution strategies (like In-line) result in different durations for each stock within a trade-list. As a reuslt, weights are also changing throughout the day – which affects the correlation benefits of the remaining trade. The impacty of residuals changing over time, thanks to different durations of stock level execution strategies (see exhibit 33).

Our risk estimates take these dynamic exposures and weight changes into account – both from the perspective of risk reduction and the impact on correlations at each point in time

- **★** EDGE allows users to chose execution strategy:
 - VWAP allows users to 'duration match' portfolio executions
 - INLINE minimise residual risks for a set aggression level



Adjustments for Dynamic Exposures

Portfolio volatility is calculated from an exponentially weighted covariance matrix scaled by a duration matrix which intends to express the time of interaction between the stocks of the portfolio.

However we highlight that although this includes the changes to diversification as more liquid orders complete earlier (see exhibit 34) – it does not include the delta risks created when portfolios with lop-sided buy-sell liquidity are executed in-line. Consequently, for these baskets, execution risk could be higher on days with strong market moves. Hedging delta with futures should reduce this additional risk.

Calculating Correlation for Working Trades

The methodology we used is the equivalent of the single stock risk inventory framework (computed with 90 days historical prices with an exponential decay so more recent dates count more) at the portfolio level. We also assume that the portfolio notional is decaying linearly with time.

For a portfolio:

If
$$P(t) = P_0 \times (\sum_i (w_i \times (1 - t / D_i)))$$

with wi the initial weight of stock i and Di the duration of the trade of stock i, the inventory risk

$$R = P_0 \times \sqrt{\left(\sum \sum w_i w_j \times TimeFactor_{ij} \times cov_{ij}\right)}$$

where

$$TimeFactor_{ij} = \min(D_i, D_j) - ((\frac{1}{D_i} + \frac{1}{D_j}) \times (\frac{\min(D_i, D_j)^2}{2})) + (\frac{\min(D_i, D_j)^3}{(3 \times D_i \times D_j)})$$

This time factor reflects the fact that each pair of stocks is interacting for a period which is a function the stocks' durations.



APPENDIX: Using the new PreTrade in EDGE

Can't Log-in to EDGE?

Not Permissioned?

This website is only for clients. If you are a client, and you want access:

 Send your contact info and CS salesperson's name to: portfolio.derivativesstrategy@credit-suisse.com

Forgot Your Password or Username?

If you can't remember your Credit Suisse web username**:

- Enter your email address in the "forgot your password" box
- Click Go.

We will resend your username, and send a <u>new</u> password – which will work for all Credit Suisse applications you are subscribed to.

(**Note: this will <u>RESET your current password</u> for <u>ALL other</u> Credit Suisse websites too).

Accessing the Model Online

A beta version of our new pre-trade model is available online as part of our EDGE website: <u>www.credit-suisse.com/edge</u>. Edge allows users to:

- Upload & save their own portfolios
- Test the way various aggression levels affect expected trade costs and execution risks (confidence bands)
- Compare inline an VWAP executions
- Analyse key trade risks including highlighting country, sector, spread, volatility and impact exposures,
- See key stocks to watch in a tradelist including those with the highest required liquidity, most impact, highest spreads and highest volatility

Existing EDGE users who would like access to these new Portfolio pages should contact their CS salesperson.

Users who don't have access to EDGE, or have forgotten their password, can follow the steps in the grey box (left).

Automatically Link Program Trades & EDGE

All program trading clients can access live fills and intra-trade performance in the TradeView (included in EDGE > Trading menu > View Lists. See exhibit A1). Talk to your Program Trading salesperson for access or information.

TradeView is now incorporated into EDGE. Traders can run live portfolio PreTrades in EDGE using the following simple steps:

- 1. Send your Portfolio Trade to Credit Suisse's Program Trading or Transitions desks. Request that they 'web enable' your lists.
- 2. In the Lists section of TradeView, click on the live portfolios you wish to import, and press the "import" button.
- 3. A popup will appear confirming your choices press the "Start Importing" button.
- Return to the EDGE > Portfolios section. These portfolios should now be in your "MyLists" page, and available in all portfolio analytics pages – including in the Portfolio dropdown in Pretrade page.

CREDIT SUISSE	EDGE ^β										
SEARCH TRADE ID		IOS TRADING	RESOURCES								-
		PRICE Trading Lists)			Vie	w Lists				
Lists Super Lists		View Lists	5								
CUSTOMER: AAA		Market Watch Market Guide									
🔂 Merge 📉 Import	Portfolio Name	T Market holida	ys Total Value	Total Shares	Total Names	% Complete	Performance	vs VWAP	BPS/CPS	Executed Value	Execute
	/						Executed	Leaves	Total		
✓ ×	TOTALS		1,679,870.40	561,339	30	3.31%	-66.96	198.99	190.34	55,571.53	559
`~□← -	pls dont remove this basket	Tue, 21 Jul 2009	115.08	14	14	0.00%	0.00	-29.41	-29.41	0.00	
			Sources Credi			21 1		1			

Source: Credit Suisse: Portfolio Strategy

17

Exhibit A1: PreTrade Details



Marking to Market

Our PreTrade uses:

- Live mid-price is used to calculate positions, consistent with our impact model.
- 21 day average Volumes to calculate liquidity (US volumes are consolidated)
- Spreads that are collected every 10 mins while markets are open, then exponentially weighted so they have a half-life of just over 2 hours - similar in duration to many larger trades, but long enough to include the increase in spreads at open and close.
- Our costs curves have been calibrated using the data discussed in: Evolution of Impact Cost Models and Estimating Execution Costs reports.

More details will be available in a report dedicated to our PreTrade model, once the Beta version is finalized.

INLINE or VWAP?

Although INLINE execution strategies will reduce gross market exposure faster - they may also create delta - as the scenario below. for a cash-neutral trade shows (Delta = red line, gross exposure = red area).

Although a VWAP strategy has a slower execution profile, the chart shows that it minimizes delta for this trade at all points.

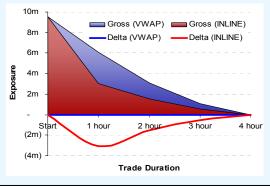


Exhibit A2: PreTrade Choices

Beta PreTrade Tools

Trade planning and execution cost benchmarking are very important tools for investors. Credit Suisse currently offers clients a choice of impact cost models - via our Doctor Portfolio and PRICE systems. Each model takes a different approach in impact cost calculation. The different strengths and weaknesses of each model are discussed in Evolution of Impact Cost Models:

- Doctor Portfolio is an inventory cost model
- Price is a semi-empiracle model, similar to the Almgren and Chriss model

In our latest release of EDGE, we have included a Beta version of a new, recalibrated, pre-trade model. Basic details of the model are included in the grey sidebar on this page - but more details will be available in a report dedicated to our PreTrade model, soon.

Impact Cost Modelling

Traders know that trading is, in fact, a 'trade-off'.

- Executing more quickly will reduce your exposure to market risk, but will increase impact and reduce opportunities to attract offsetting liquidity.
- Executing more slowly has less impact, but far more exposure to trends, and potentially results in more signalling.

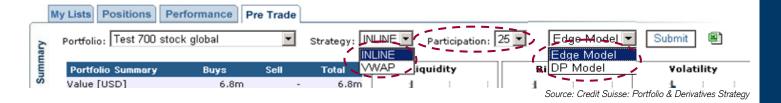
We discussed the common approaches to modeling impact cost in our recent report: Evolution of Impact Cost Models. Overall, most impact models focus too much on volatility as a cost (volatility is really more about execution risk) and lack an alpha component (which is mostly what makes you trade).

EDGE Models = New Choices

Our beta EDGE PreTrade includes unique flexibility for traders to compare impact cost for global portfolios or trades, across:

- A choice of model: We include our existing Doctor Portfolio (inventory cost) model - with enhanced trade-date data - as well as our new empirical model (labeled the EDGE model).
- A choice of execution style: EDGE allows traders to compare how cost & execution risk changes as the switch between VWAP and INLINE strategies - and different levels of aggression - giving traders more information before they start trading.

Almgren/Chriss methodology typically computes optimal execution on a stock-by-stock basis - which results in each order being worked 'in line' regardless of holistic portfolio risk. However for many trade lists (especially quantitative funds and delta-neutral trades) can benefit from being executed at a consistent rate, as this minimizes trend risk and factor dislocation during the day. At a minimum this reduces unwanted delta over time (see blue side-bar).





Pre-Trade Summary - Focus your Time!

To make it easy to identify issues, the pre-trade tab has a summary screen that summarizes important components of your trade:

- Profiles of impact, Liquidity, Spreads and volatility: These highlight where significant portions of your trade list, by value, could be difficult to trade efficiently – which helps deciding what execution strategy to use
- Stock Highlights: Our "top 5" lists highlight the stocks that are most likely to need special trading and focus. This will help traders extract better executions from a large list, without becoming overly complex
- Impact estimates: Using our recently recalibrated impact model we show what the "average" similar execution has cost a valuable bogey for traders trying to measure their own impact, and execution performance, as the day progresses.
- Risk & Exposures: The Portfolio & Impact summary sections highlight important information about your overall trade – including total delta liquidity, spreads and costs. These can help decide whether a shortfall execution strategy will work better than a VWAP execution.
- Sector and Country Exposures: Knowing sector and country exposures, especially in this volatile & macro driven market, also helps manage overall portfolio slippage.

	ISSE EDG								-		_	-			-		
ARCH T	RADE IDEAS	OPTIONS P	ORTFOLIC	JS TR	RADING	RESOL	JRCES						May 12	2009	PMACKI	ντj	Logo
My Lists Po	ositions Perform	ance Pre Tra	ide														
			-					_				-					
Portfolio:	TEST Global Titans	s (\$10bn L/S)	Str	ategy: IN	ILINE 💌	Participa	tion: 25	•	Edg	je Model 💌	Submit	8					
Portfolio	Summary	Buys	Sell	1	Total	Lic	quidity			Bid-Ask		Volat	tility		Imp	act	
Value (USI	D]	7.8b	2	2.3Ь	10.1b		1 1					4					
Shares		399,859,420	98,623,	249 498	3,482,669	15D+			15D+		1504	1			15D+		
Names		34		11	45	100-150 -			100-150 -		10D-15			10	D-150 -		
Liquidity (%]	40.84	43	3.34	41.41	75-10D			75-10D		75-1D	4		7	S-100		
Max Durat		3,49		3.37	3.49	5D-75 -			50-75		5D-7				5D-75		
Wtd Ave D		1.63		1.73	1.66												
		9,79		2.09	10.31	25-5D	- 200 - 100: -	3	25-5D		25-5				25-50		
Wtd Bid-a		9.79	14			1D-25			10-25		1D-2				1D-25		
Impact Su				8	Total	D-1D			D-1D		D-11	Γ.			D-10		
	Spread Cost (bps, fr	om mid)			2.63	0.10			0.10		0.11	-			0.10		
Denter Line 1					and the second	E .					_						
Portrollo M	Market Impact (bps)				91.55	E.	2D 4D	6D	D) 5D	_	0	SD		D	ZD	40
	Market Impact (bps) Impact Cost (bps				and the second		ZD 4D oss Weigh		D C	sø Gross Weight [%]	D Gross	s۵ Weight [۹	5]	D Gross		40 ght [%]
Portfolio	Impact Cost (bps				91.55 94.18				D		%]	D Gross		- 6]	D Gros		
Portfolio	Impact Cost (bps Deviation (+/- bps)				91.55				0		%]	Gross		•]	B Gross		
Portfolio Standard	Impact Cost (bps Deviation (+/- bps)			Sells	91.55 94.18 92.86				G	Gross Weight [%]	D Gross	Weight (%)		Sell	s Wein	
Portfolio Standard COST + R Buys Largest Po	Impact Cost (bps Deviation (+/- bps) RISK (bps) ositions)		Largest I	91.55 94.18 92.86 187.04 Positions	Gro	oss Weigh	nt [%]	G	Gross Weight [Se	ctors	D Gross	Weight (%) Buy # Weigl	nt#	Sell Weight	s Wein #	ght [%] Fotal Weigh
Portfolio Standard COST + R Buys Largest Po Ric	Impact Cost (bps) Deviation (+/- bps) USK (bps) ositions Value[USD] Wo) eight[%] Impact		Largest I Ric	91.55 94.18 92.86 187.04 Positions Value [Gro [USD] We	oss Weigh aight [%]	nt [%]		Gross Weight [Se Basic Material	ctors s	D Gross	Weight [% Buy # Weigh 1 0.9	nt # 4 1	Sell Weight	s Wei # 2	ght [%] Fotal Weigh 2.83
Portfolio Standard COST + R Buys Largest Pa Ric XOM.N	Impact Cost (bps Deviation (+/- bps) VISK (bps) ositions Value[USD] We 799,734,228) sight[%] Impact 7.893	82	Largest I Ric GE.N	91.55 94.18 92.86 187.04 Positions Value [(303,8	Gro (USD] We (397,186)	oss Weigh eight [%] (2.999)	Impact	113	Gross Weight [Se Basic Material Communicatio	ctors s ns		Weight [% Buy # Weigh 1 0.9 5 10.1	nt # 4 1 0 1	Sell Weight 1.94 1.91	s Wei # 2 6	ght [%] Fotal Weight 2.88 12.00
Portfolio Standard COST + R Buys Largest Po Ric	Impact Cost (bps) Deviation (+/- bps) USK (bps) ositions Value[USD] Wo) eight[%] Impact		Largest I Ric	91.55 94.18 92.86 187.04 Positions Value [(303,8 < (265,0	Gro [USD] We	oss Weigh aight [%]	Impact		Gross Weight [Se Basic Material	ctors s ns clical		Weight [% Buy # Weigh 1 0.9	nt # 4 1 0 1 3 0	Sell Weight	s Wein # 2 6 1	ght [%] Fotal Weight 2.88
Portfolio Standard COST + R Buys Largest Po Ric XOM.N MSFT.OQ JNJ.N T.N	Impact Cost (bps) Deviation (+/- bps) NISK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161) eight[%] Impact 7.893 3.476 3.361 3.352	82 109 65 95	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX	91.55 94.18 92.86 187.04 Positions Value [(303,8 <(265,0) 2 (247,1) (196,1	Gro USD] We 397,186) 076,941) 163,424) 112,112)	eight [%] (2,999) (2,616) (2,439) (1,935)	Impact	113 72 37 110	Sross Weight [Se Basic Material Communicatio Consumer, Cyo Consumer, No Energy	ctors s ns clical		Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9	nt # 4 1 3 0 6 3 6 1	Sell Weight 1.94 1.91 0.00 6.20 1.92	# 2 6 1 13 9	ght [%] Total Weigh 2.83 12.00 2.73 28.97 23.87
Portfolio Standard COST + R Largest Pa Ric XOM.N MSFT.OQ JNJ.N T.N PG.N	Impact Cost (bps) Deviation (+/- bps) USK (bps) Value[USD] W 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024) eight[%] Impact 7.893 3.476 3.361	82 109 65	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS	91.55 94.18 92.86 187.04 Positions Value [(303,8 < (265,0 2 (247,1) (196,1 (194,6	Gro USD] We 397,186) 076,941) 163,424) 112,112) 594,160)	eight [%] (2,999) (2,616) (2,439)	Impact	113 72 37	Sross Weight [Basic Material Communicatio Consumer, Cy Consumer, Nor Energy Financial	ctors s ns clical		Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0	nt # 4 1 3 0 6 3 6 1 9 1	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68	# 2 6 1 13 9 6	ght [%] Fotal Weigh 2.8: 12.00 2.7: 28.9 23.8° 10.70
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.0Q JNJ.N T.N PG.N Most Illiqu	Impact Cost (bps Deviation (+/- bps) USK (bps) Value [USD] Wo 799,734,228 352,247,456 340,524,802 339,627,161 335,705,064 335,705,064 add Positions) sight[%] Impact 7.893 3.476 3.361 3.352 3.313	82 109 65 95 92	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq	91.55 94.18 92.86 187.04 Positions Value [(303,8 (265,0 2) (247,1 (196,1) (194,6 quid Positic	Gro Gro Gro Gro Gro Gro Gro Gro	eight [%] (2.999) (2.616) (2.439) (1.935) (1.922)	Impact	113 72 37 110	Sross Weight [Basic Material Communicatio Consumer, Cyo Consumer, Nor Energy Financial Technology	ctors s ns clical		Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5	nt # 4 1 0 1 3 0 6 3 6 1 9 1 0 3	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68 5.92	# 2 6 1 13 9 6 6	ght [%] Total Weigh 2.8 12.00 2.7 28.9 28.9 28.9 10.7 14.4 3
Portfolio Standard COST + R Largest Pa Ric XOM.N MSFT.OQ JNJ.N T.N PG.N	Impact Cost (bp; Deviation (+/- bps) UISK (bp;) value[USD] Wales[USD] wasser 352;247.456 340,524.802 339,627.161 335,705,024 uid Positions % Daily Yol) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight [%] Impact	82 109 65 95 92	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric	91.55 94.18 92.86 187.04 Positions Value [(303,8 (265,0) 2 (247,1 (196,1 (194,6 quid Positic % Daily	Gra (USD] We 397,186) 176,941) 163,424) 112,112) 1	eight [%] (2,999) (2,616) (2,439) (1,935) (1,922) eight [%]	Impact	113 72 37 110	Sross Weight [Basic Material Communicatio Consumer, Cy Consumer, Nor Energy Financial	ctors s ns clical		Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5	nt # 4 1 0 1 3 0 6 3 6 1 9 1 0 3 5 0	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68	# 2 6 1 13 9 6 6 1	ght [%] Total Weigh 2.8 12.0 2.7 28.9 23.8 10.7 14.4 1.3 3
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L	Impact Cost (bps) Deviation (+/- bps) UISK (bps) value[USD] Wales[USD] wasser 352,247,456 340,524,802 339,627,161 335,705,024 wasser % Daily Yol % Daily Yol) eight[%] Impact 7.893 3.476 3.361 3.352 3.313 eight [%] Impact 3.245 2.014	82 109 65 95 92 1 85 93	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA	91.55 94.18 92.86 187.04 Positions Value [(303,8 < (265,0 2 (247,1 (196,1 (194,6 (194,6 (194,6) (194,	Gro USD] We 397,186) 076,941) 63,424) 112,112) 594,160) DNS 940 84,35 69.05	eight [%] (2.999) (2.616) (2.439) (1.935) (1.922) eight [%] (1.922) (1.731)	Impact	113 72 37 110 94 94 98	Sross Weight [Basic Material Comsuncatio Consumer, No Consumer, No Co	ctors s ns clical	9	Buy Weight [9 Weight 1 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0	nt # 4 1 0 1 3 0 6 3 6 1 9 1 0 3 5 0	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68 5.92 0.00	# 2 6 1 13 9 6 6 1 1	ght [%] Fotal Weigh 2.8 12.0 2.8 12.0 2.8 12.0 2.8 12.0 2.8 1.2 3.8 1.0 7 1.4 3.0 0 3.0 0 3.0 0 3.0 0 3.0 0 3.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1
Portfolio Standard COST + R Buys Largest Po Ric XOM.N MSFT.0Q JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L NESN.VXX	Impact Cost (bps Deviation (+/- bps) USK (bps) Value[USD] WV 799,734,228 335,2247,456 340,524,802 339,627,161 335,705,024 339,627,161 % Daily Vol WV %7,36 79,6 75,2) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight[%] Impact 3.245 2.014 3.133	82 109 65 95 92 85 93 78	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX	91.55 94.18 92.86 187.04 Positions Value [(303,8 < (265,0 2 (247,1 (196,1 (194,6 (194,6 (194,6) (194,	Gro USD] We 397,186) 776,941) 163,424) 112,112) 594,160) DNS 84,35 69,05 66,75	eight [%] (2,999) (2,616) (2,439) (1,935) (1,922) eight [%] (1,922) (1,731) (2,616)	Impact	113 72 37 110 94 94 98 72	Sross Weight [Basic Material Communicatio Consumer, Cy- Consumer, No Energy Financial Technology Utilities Industrial Total	ctors s ns clical n-Cyc.,	3	Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4	nt # 4 1 3 0 6 3 9 1 0 3 5 0 0 1 3 11	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68 5.92 0.00 3.00 22.57	s Wein # 2 6 1 13 9 6 1 1 45	Ght [%] Veigh 2.83 12.00 28.97 10.77 14.43 3.00 100.01
Portfolio Standard COST + R Buys Largest P4 Ric XOM.N MSFT.0Q JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L NESN.VX	Impact Cost (bps) Deviation (+/- bps) UISK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024 % Daily Vol % Daily Vol 79,6 75,2 69,43) eight[%] Impact 7.893 3.476 3.361 3.352 3.313 eight [%] Impact 3.245 2.014 3.133 2.181	82 109 65 95 92 85 93 78 101	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX BHP.AX	91.55 94.18 92.86 187.04 Positions Value [(303,8 < (265,0 2 (247,1 (196,1 (194,6 (194,6 (194,6) (194,	Gra 050] We 097,186) 076,941) 112,112) 094,160) 008 94,160) 008 84,35 69,05 69,05 69,05 55,23	<pre>sight [%] (2.999) (2.616) (2.439) (1.935) (1.935) (1.922) (1.731) (2.616) (1.935)</pre>	Impact	113 72 37 110 94 94 98 72 110	Sross Weight [Basic Material Communicatio Consumer, Cyu Consumer, Nor Energy Financial Technology Utilities Industrial	ctors s ns clical n-Cyc.,	3	Buy # Weight [9 # Weigh 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Buy	nt # 4 1 3 0 6 3 9 1 0 3 5 0 0 1 3 11 3 11	Sell Weight 1.94 1.91 0.00 6.20 1.92 1.68 5.92 0.00 3.00 22.57 Sell	s Wein # 2 6 1 13 9 6 1 1 1 4 5	Cotal Weigh 2.83 12.00 2.73 28.99 23.83 10.74 14.43 3.00 100.00 0001
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L NESN.VX VOD.L TOTE.PA	Impact Cost (bps) Deviation (+/- bps) UISK (bps) ositions Value[USD] Way 799,734,228 352,247,456 340,524,802 338,627,161 338,750,204 wide Positions % Daily ON W136 79.6 75.2 69.43 57.57) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight[%] Impact 3.245 2.014 3.133	82 109 65 95 92 85 93 78	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX BHP.AX	91.55 94.18 92.86 187.04 Positions Value [(303,8 (265,0) (247,1) (194	Gru (USD] We (397,186) 176,941) 163,424) 112,112, 112,112, 1594,160) Ons y Vol We 84,35 69,05 69,05 55,23 52,28	eight [%] (2,999) (2,616) (2,439) (1,935) (1,922) eight [%] (1,922) (1,731) (2,616)	Impact	113 72 37 110 94 94 98 72	Sross Weight [Source of the second of the s	ctors s ns clical n-Cyc.,	;	Buy # Weight 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77,4 Buy Weight	nt # 4 1 3 0 6 3 6 1 9 1 0 3 5 0 1 3 11 3 11 5 3 #	Sell Weight 1.94 1.91 0.000 6.20 1.68 5.92 0.000 3.000 22.57 Sell Weight	s Wein # 2 6 1 13 9 6 1 1 1 45	Ght [%] Weigh 2.8 12.0 2.7 28.9 23.8 10.7 14.4 1.3 3.0 100.0 otal Weigh
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L NESN.VX VOD.L TOTE.PA	Impact Cost (bps) Deviation (+/- bps) UISK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024 % Daily Vol % Daily Vol 79,6 75,2 69,43) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight [%] Impact 3.245 2.014 3.133 2.181 2.585	82 109 65 95 92 85 93 78 101 96	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX BHP.AX	91.55 94.18 92.86 187.04 Positions Value [(303.8 (265.0 2 (247.1) (194.6 (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (196	Gru (USD] We (397,186) 176,941) 163,424) 112,112, 112,112, 1594,160) Ons y Vol We 84,35 69,05 69,05 55,23 52,28	<pre>cight [%] (2,999) (2,616) (2,439) (1,932) (1,922) cight [%] (1,922) (1,731) (2,616) (1,935) (1,857)</pre>	Impact	113 72 37 110 94 94 98 72 110	Sross Weight [Basic Material Communicatio Consumer, Cy Consumer, No Energy Financial Technology Utilities Industrial Total Brazil	ctors s ns clical n-Cyc.,	3	Buy # Weight 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Buy Weight	nt # 4 1 0 1 3 0 6 3 6 1 9 1 0 3 5 0 1 3 11 3 11 8 9 4 0	Sell Weight 1.94 1.91 0.000 6.20 1.92 1.68 5.92 0.00 3.00 3.00 22.57 Cell Weight 0.00	s Wein # 2 6 1 13 9 6 1 1 1 4 5	ght [%] Veigh 2.87 2.89 23.87 23.87 23.87 14.42 1.33 3.00 100.00 0tal Weigh 1.0°
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N Most Illiqu Ric SK.L NESN.VX VOD.L TOTE.PA Largest Bi Ric ABT.N	Impact Cost (bps Deviation (+/- bps) USK (bps) Value[USD] W 799,734,228 335,2247,456 340,524,802 339,627,161 335,705,024 339,627,161 335,705,024 40 Bid-Ask [as] W 87.36 75.2 69,43 57,57 id-Ask Spread Bid-Ask [bps] W 23,91) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight[%] Impact 1.539 sight[%] Impact 1.539	82 109 65 95 92 92 85 93 78 101 96 90.75	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX BHP.AX PM.N Largest I Ric PM.N	91.55 94.18 92.86 187.04 Positions Value [(303.8 (265.0 2 (247.1) (194.6 (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (196	Grt USD] We 397,186) 376,941) 163,424) 112,112) 394,160) Ons 84.35 59,05 66.75 52,88 S2,88 oread k [Bp] We 39.25	<pre>sight [%] [2,999] (2,616) (2,439) (1,932) (1,932) (1,932) (1,932) (1,932) (1,935) (1,935) (1,857) sight [%] (1,857)</pre>	Impact	113 72 37 110 94 98 72 110 111 111	Sross Weight [Basic Material Communicatio Consumer, Cy- Consumer, Not Energy Financial Technology Utilities Industrial Total Brazil Finand	ctors s ns clical n-Cyc.,	;	Buy # Weight 1 0.9 5 10.1 1 2.7 0 22.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77,4 Buy Weight	nt # 4 1 3 0 6 3 6 1 9 1 0 3 5 0 1 3 11 3 11 5 3 #	Sell Weight 1.94 1.91 0.000 6.20 1.68 5.92 0.000 3.000 22.57 Sell Weight	s Wein # 2 6 1 13 9 6 1 1 1 45	cotal Weigh 2.8: 12.00 2.7: 28.9 ⁹ 23.8: 10.7: 14.4: 1.3: 3.00 100.00 0tal Weigh 1.0 ¹ 1.1 ¹
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N MOST IIIQU Ric BP.L GSK.L NESN.VX VOD.L TOTF.PA Largest Bi Ric ABT.N T.N	Impact Cost (bp) Deviation (+/- bps) UISK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024 % Daily Vol W4 87,36 75,22 69,43 57,57 id-Ask Spread Bid-Ask [Eps] W4 23,91) eight[%] Impact 7.893 3.476 3.361 3.352 3.313 eight [%] Impact 3.245 2.014 3.133 2.181 2.585 eight [%] Impact 1.539 3.352	82 109 65 95 92 85 93 78 101 96 96 90,75 94,97	Largest I Ric GE,N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS SASY.PA NOVN.VX BHP.AX PM.N Largest I Ric PM.N VZ.N	91.55 94.18 92.86 187.04 Positions Value [(303.8 (265.0 2 (247.1) (194.6 (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (196	Gri (USD] We 397,166) 776,941) 163,424) 112,112) 594,160) ons 84,35 69,05 52,28 52,29 52,28 52	<pre>sight [%] (2.999) (2.616) (2.439) (1.935) (1.935) (1.922) sight [%] (1.922) (1.731) (2.616) (1.923) (1.857) (1.857) (1.857)</pre>	Impact	113 72 37 110 94 94 98 72 110 111 110.71 78.60	Sross Weight [Basic Material Communicatio Consumer, Not Energy Financial Technology Utilities Industrial Total Finand France Germany	ctors s ns clical n-Cyc.,	# 1 1	Buy # Weight 1 0.7 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Suy Weight 1.07 1.17 4.74 2.38	nt # 4 1 0 1 3 0 6 1 9 1 0 3 5 0 1 0 3 5 0 1 3 11 3 11 3 11 3 11 1 0 1 0	Sell Weight 1.94 1.91 1.92 1.68 5.92 0.00 3.000 22.57 Sell Weight 0.00 0.00 1.73 0.00	s Wein # 2 6 1 1 3 9 6 6 1 1 1 4 5 7 7 # 1 1 4 2	cotal Weigh 2.83 12.00 23.83 10.77 14.43 1.03 3.00 100.00 cotal Weigh 1.00 1.11 6.44 2.33
Portfolio Standard COST + R Largest Pe Ric XOM.N MSFT.0Q JNJ.N T.N PG.N Most Illiqu Ric BP.L GSK.L NESN.VX VOD.L TOTF.PA Largest Bi Ric ABT.N T.N PFE.N	Impact Cost (bps) Deviation (+/- bps) UISK (bps) Value[USD] W 799,734,228 332,247,456 340,524,802 339,627,161 335,705,024 339,627,161 335,705,024 did Positions % Daily Vol Wo 87,36 79,6 75,2 69,43 57,57 id.Ask Spread Bid-Ask [Bps] Wo 23,91 22,31 18,75) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight[%] Impact 3.245 2.014 3.133 2.181 2.181 1.539 3.352 sight[%] Impact	82 109 95 92 * * * * * * * * * * * * * * * * * *	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX MOSH.OQ BHP.AX ROSa.AS SASY.PA NOVN.VX BHP.AX PM.N Largest I Ric PM.N V2.N V2.N	91.55 94.18 92.86 187.04 Positions Value [(303.8 (265.0 2 (247.1) (194.6 (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (194.6) (196	Gri USD] We 397,156) 776,941) 163,424) 112,112) 394,160) Ons 4,35 69,05 69,05 52,28 55,58 55,58 55,58 55,58 55,58 55,58 55,58 55,5	<pre>sight [%] (2,999) (2,616) (2,439) (1,935) (1,935) (1,932) (1,935) (1,935) (1,935) (1,935) (1,857) (1,857) (1,936) (1,676)</pre>	Impact	113 72 37 110 94 98 72 110 111 110.71 18.60 146.85	Sross Weight [Basic Material Communicatio Consumer, Cy- Consumer, Not Energy Financial Technology Utilities Industrial Total Brazil Finland F	ctors s ns clical n-Cyc.,	# 1 1 3 2 1	Buy # Weight 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Suy Weight 1.07 1.17 1.72 2.38 1.25 1.25	t # 4 1 0 1 6 3 6 1 9 1 0 6 3 11 3 11 8 8 7 0 0 1 0 0 0	Sell Weight 1.94 1.91 0.00 6.20 1.68 5.92 0.00 3.00 3.00 22.57 cell Weight 0.00 0.00 1.73 0.00	s Wein # 2 6 1 1 3 9 6 6 1 1 1 4 5 7 7 7 7 1 1 4 5	ght [%] Veigh 2.8 12.0 2.7 28.9 20.0 10.0 0 0 0 0 0 0 0 0 1.0 1.
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N MOST Illiqu Ric BP.L GSK.L NESN.VX VOD.L TOTF.PA Largest Bi Ric ABT.N T.N	Impact Cost (bp) Deviation (+/- bps) UISK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024 % Daily Vol W4 87,36 75,22 69,43 57,57 id-Ask Spread Bid-Ask [Eps] W4 23,91) eight[%] Impact 7.893 3.476 3.361 3.352 3.313 eight [%] Impact 3.245 2.014 3.133 2.181 2.585 eight [%] Impact 1.539 3.352	82 109 65 95 92 85 93 788 101 96 96 90.75 94.97 81.59 64.92	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RSAS.PA NOVN.VX BHP.AX PM.N Largest I Ric BHP.AX PM.N V2.N	91.55 94.18 92.86 187.04 Positions Value [(205.0 (247.1) (194.6 (194.6 Quid Positic) % Daily	Gri (USD] We 397,166) 776,941) 163,424) 112,112) 594,160) ons 84,35 69,05 52,28 52,29 52,28 52	<pre>sight [%] (2.999) (2.616) (2.439) (1.935) (1.922) sight [%] (1.922) (1.731) (2.616) (1.935) (1.857) (1.857) (1.857) (1.857) (1.857) (1.676) (1.676)</pre>	Impact	113 72 37 110 94 94 94 94 94 94 94 94 94 94 94 94 94	Sross Weight [See Basic Material Communicatio Consumer, Nor Energy Financial Technology Utilities Industrial Total Brazil Finland France Germany Italy Switzerland	ctors s ns clical h-Cyc., ries	# 1 3 2 1 2	Buy # Weight 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Suy Weight 1.07 1.17 4.74 2.38 1.25 5.40	nt # 4 1 3 0 6 3 6 1 9 3 5 0 0 3 11 3 11 3 11 0 3 11 1 0 0 1 0 1	Sell Weight 1.94 1.91 1.92 1.68 5.92 0.00 22.57 Cell Weight 0.00 0.00 1.73 0.00 1.73 0.00 2.62	s Wein * 2 6 1 1 3 9 6 6 1 1 4 5 * * 1 1 4 5 * * * * * * * * * * * * *	cotal Weigh 2.8 12.0 2.7 23.9 23.8 10.7 14.4 1.3 3.0 100.0 0tal 0tal 0tal 0.1 1.1 6.4 2.3 1.2 8.0
Portfolio Standard COST + R Largest Pr Ric XOM.N MSTF.0Q JNJ.N T.N MOST IIIqu Ric BP.L GSK.L NESN.VX VOD.L TOTF.PA Largest Bi Ric ABT.N T.N PFE.N JNJ.N PFE.N	Impact Cost (bps) Deviation (+/- bps) USK (bps) Value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 339,705,024 % Daily Vol W4 % Daily Vol W4 87,36 75,25 69,43 57,557 id-Ask Spread Bid-Ask [Eps] W6 23,91 Bid-Ask [Eps] W6 23,91 18,75) eight[%] Impact 7.893 3.476 3.361 3.352 3.313 eight [%] Impact 3.133 2.181 2.585 eight [%] Impact 1.539 3.352 2.212 3.361	82 109 95 92 * * * * * * * * * * * * * * * * * *	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS SASV.PA NOVN.VX BHP.AX PM.N Largest I Ric PM.N 8306.T HPQ.N ORCLOQ	91.55 94.18 92.86 187.04 Positions Value [(205.0 (247.1) (194.6 (194.6 Quid Positic) % Daily	Gri USD] We 397,166) 176,941) 163,424) 112,112) 94,160) 09,05 69,05 69,05 69,05 69,05 52,288 52,288 52,283 52,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,295 55,2	<pre>sight [%] (2,999) (2,616) (2,439) (1,935) (1,935) (1,932) (1,935) (1,935) (1,935) (1,935) (1,857) (1,857) (1,936) (1,676)</pre>	Impact	113 72 37 110 94 98 72 110 111 110.71 18.60 146.85	Sross Weight [Basic Material Communicatio Consumer, Co- Consumer, Not Energy Financial Technology Utilities Industrial Total Brazil Finland France Germany Italy Switzerland United Kingdor	ctors s ns clical h-Cyc., ries	↓ 1 1 3 2 1 2 5	Buy # Weight 0.9 5 1 0.7 22.7 3 6 1 3 0 0.03 8.21.9 1 3 0 0.034 Weight 1.07 1.17 1.07 1.17 1.474 2.38 1.25 5.40 10.633	nt # 4 1 3 0 6 3 5 0 0 1 3 11 8 7 0 1 0 0 1 0 0 1 0 0	Sell Weight 1,94 1,91 0,00 6,20 1,92 1,68 5,92 0,00 3,00 3,00 22,57 cell Weight Weight 0,00 0,00 0,00 0,00 0,00 0,00 0,00 0,	s Wein # 2 6 1 1 3 9 6 1 1 4 5 5	ght [%] Fotal Weigh 2.8 12.0 2.7 28.9 23.8 10.7 14.4 1.3 3.00 100.0 otal Weigh 1.0 1.1 6.4 2.3 1.2 8.0 10.0 10.6 1.2 1.2 1.2 1.2 1.2 1.2 1.2 1.2
Portfolio Standard COST + R Largest PL Ric XOM.N MSFT.OQ JNJ.N T.N PG.N MOST IIIQU Ric BP.L GSK.L NESN.VX VED.L TOTF.PA Largest BI Ric ABT.N T.N PFE.N JNJ.N PG.N MOST VOIA Ric	Impact Cost (bp) Deviation (+/- bps) UISK (bps) value[USD] W4 799,734,228 352,247,456 340,524,802 339,627,161 335,705,024 345,705,705 345,705,705 345,705,705 345,705,705,705,705,705,705,705,705,705,70) sight[%] Impact 7.893 3.476 3.352 3.313 sight [%] Impact 3.245 2.014 3.133 2.181 2.585 sight [%] Impact 1.539 2.212 3.361 3.313 sight [%] Impact	82 109 65 95 92 85 93 78 101 96 90.75 94.97 81.59 94.97 81.59 94.92 92.38	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illig Ric RDSa.AS SASY.PA NOVN.VX BHP.AX PM.N Largest I Ric VZ.N 8306.T HPQ.N ORCLOQ Most Vol Ric	91.55 94.18 92.86 187.04 Positions Value [(205.0 (247.1) (194.6 (194.6 (194.6 Walther and the second s	Gri 397,186) 776,941) 163,424) 112,112, 594,160) ons 84,35 69,05 55,23 55,238 oread 8(Bps] We 39,25 20,02 13,60 10,28 ions ion	<pre>sight[%] (2,999) (2,616) (2,439) (1,932) (1,932) (1,922) sight[%] (1,922) (1,731) (2,616) (1,922) (1,731) (2,616) (1,922) (1,857)</pre>	Impact	113 72 37 110 94 98 72 110 111 110.71 78.60 146.85 111.18 79.96	Sross Weight [See Basic Material Communicatio Consumer, Nor Energy Financial Technology Utilities Industrial Total Brazil Finland France Germany Italy Switzerland	ctors s ns clical h-Cyc., ries	# 1 3 2 1 2	Buy # Weight 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0 34 77.4 Suy Weight 1.07 1.17 4.74 2.38 1.25 5.40	nt # 4 1 3 0 6 3 6 1 9 3 5 0 0 3 11 3 11 3 11 0 3 11 1 0 0 1 0 1	Sell Weight 1.94 1.91 1.92 1.68 5.92 0.00 0.00 3.00 22.57 Sell Weight 0.00 0.00 1.73 0.00 0.00 0.00 2.62 0.00 0.00 0.00	s Wein # 2 6 1 1 3 9 6 1 1 4 5 5	ght [%] Fotal Weigh 2.8.9 2.8.9 2.3.8 10.7 2.8.9 2.3.8 10.7 1.4.4 1.0 3.00 tol Weigh 1.0 tol Weigh 1.0 tol Weigh 1.0 tol Weigh 1.0 tol Weigh 1.0 tol Weigh 1.0 tol Weigh 1.0 tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol tol
Portfolio Standard COST + R Largest Pr Ric XOM.N MSFT.OQ JNJ.N T.N PG.N Most Illiqu Ric ABT.N TOTF.PA Largest Bi Ric ABT.N T.N PFE.N JNJ.N PG.N Most Vola	Impact Cost (bps) Deviation (+/- bps) USK (bps) Value[USD] WV 799,734,228 335,2247,456 340,524,802 339,627,161 335,705,024 339,627,161 335,705,024 339,627,161 87,36 79,6 87,36 79,6 79,6 79,6 79,6 87,36 79,6 79,6 79,6 79,6 79,6 79,6 79,6 79,) sight[%] Impact 7.893 3.476 3.361 3.352 3.313 sight[%] Impact 3.245 2.014 3.133 2.181 2.585 sight[%] Impact 1.539 3.352 2.212 3.361 3.313	82 109 65 95 92 8 8 8 101 96 96 90,75 94,97 81,59 64,92 92,38	Largest I Ric GE.N NOVN.VX AAPL.OQ BHP.AX RDSa.AS Most Illiq Ric RDSa.AS BHP.AX PM.N Largest I Ric Ric Ric Ric Ric Ric Ric Ric	91.55 94.18 92.86 187.04 Positions Value [(205.0 (247.1) (194.6 (194.6 (194.6 Walther and the second s	Gri (USD) We 197,196) 176,941) 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112, 112,112,112,112, 112,112,112,112, 112,112,112,112,112, 112,112,112,112,112,112,112,112,112,112	<pre>sight [%] (2.999) (2.616) (2.439) (1.932) (1.922) sight [%] (1.922) (1.731) (2.616) (1.957) (1.857) (1.857) (1.956) (1.676) (1.676) (1.676)</pre>	Impact	113 72 37 110 94 94 94 94 94 94 94 94 94 94 94 94 94	Sross Weight [Basic Material Communicatio Consumer, Cy Consumer, No Energy Financial Technology Utilities Industrial Total Brazil Finance Germany Italy Switzerland United Kingdor United States	ctors s ns clical h-Cyc., ries	# 1 1 3 2 1 1 2 5 19	Buy # Weight 1 0.9 5 10.1 1 2.7 8 21.9 5 9.0 3 8.5 1 1.3 0 0.0.0 3 8.5 1 1.3 0 0.00 3 8.7 1 1.7 1.17 1.17 1.17 4.748 1.25 5.40 10.63 50.79 0.000 50.79	nt # 4 1 0 1 3 0 6 3 9 1 0 3 5 0 1 3 11 8 7 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0	Sell Weight 1,94 1,91 1,92 1,68 5,92 0,00 22.57 Sell Weight 0,00 0,00 1,73 0,00 0,00 0,00 0,00 0,00 0,00 0,00 0	s Wein # 2 6 1 1 3 9 6 6 1 1 1 4 5 2 5 2 5	ght [%] Veigh 2.83 12.00 28.97 10.77 14.43 1.33 3.00 10.01

Exhibit A3: PreTrade Summary

Export-to-Excel

Excel spreadsheet.

Bonus Pages!

EDGE.

Where-ever you see this icon; you can

click on it to export the page into a new

The current PreTrade export incorporates the

summary, details, country & sector pages of

Source: Credit Suisse: Portfolio & Derivatives Strategy



Exhibit A4: Portfolio & Impact Summary

Portfolio Summary	Buys	Sell	Total
Value (USD)	100.8m	-	100.8m
Shares	4,984,808	-	4,984,808
Names	45	-	45
Liquidity [%]	0.41	-	0.41
Max Duration	0.03	-	0.03
Wtd Ave Duration	0.02	-	0.02
Wtd Bid-ask [bps]	7.60	-	7.60
Impact Summary			Total
Portfolio Spread Cost (bps, fro	om mid)		1.94
Portfolio Market Impact (bps)			10.34
Portfolio Impact Cost (bps)		
Standard Deviation (+/- bps)			10.59
COST + RISK (bps)			22.87

Source: Credit Suisse: Portfolio & Derivatives Strategy



Other Impact Models

For a more convenient transition, EDGE retains access to existing CS Impact models:

 Inventory Risk model: Our <u>Doctor Portfolio</u> (DP) website includes an inventory risk model. Users can access an enhanced <u>DP model</u> in the EDGE pretrade page (see the EDGE Model dropdown).

Key enhancements over the model in the Doctor Portfolio website include: faster list loading, a stock universe more than 4x broader, improved spread & volume calculators, including consolidated volumes in the increasingly disaggregated US market.

 PRICE: Our production semi-empirical model based on Almgren & Chriss' approach. PRICE is a standalone web-site, accessible for permissioned users, via the <u>Trading</u> menu in EDGE.

Market Impact Calculations

The market impact calculations in the PreTrade will differ depending on the duration and strategy of your order – and for the type of model selected – all of which are customizable is the Pretrade screen in EDGE.

Note that a VWAP execution attempts to finish all orders at the same time – so duration is fixed (the only exceptions being orders that will take more than 1 day at 50% participation). Whereas an INLINE orders fix by aggression – which means duration is specific to each stock in the list.

Assumes Zero Alpha

A key conclusion we reached in our earlier report <u>Estimating Execution Costs</u>, was that the average shortfall used to calibrate our impact model could be assumed to have close to zero alpha. We based this conclusion on the a number of factors, including the volume of orders in our sample, the fact these include buy and sell trades in the same stocks, as well as the diversity of trade strategies and signals included in our data.

Consequently, most traders should consider the <u>Portfolio Impact Cost</u> calculation as a 'base case'. As we discussed in our follow-up report <u>Evolution of Impact Cost Models</u>, most trades are also expected to have alpha, and varying rates of alpha decay. Accordingly, traders should expect additional slippage, especially for trades with high opportunity costs or using newly available information. Almgren & Chriss effectively do this by modifying their risk aversion (λ) before adding execution risk to find the optimum execution horizon.

A Beta Impact Model

The new beta impact model included in EDGE is a semi-empirical impact model (Similar to Almgren & Chriss models discussed in <u>Estimating Execution</u> <u>Costs</u>). As such, this model separates:

- Empirical costs: Shown in the Pretrade Summary as <u>Portfolio Impact</u> <u>Cost</u>. Represent a simple weighted average of single stock cost estimates (the μ in Exhibit 15). The summary breaks this cost down into the cost attributed to crossing spreads (which increases as aggression increases) and the actual movement of prices caused by the new incremental supply or demand.
- Execution risks: Shown in the Pretrade Summary as <u>Standard</u> <u>Deviation</u> (±bps). This represents the **o** in Exhibit 15, but at a portfolio level, it is adjusted for the cross correlations of stocks within the portfolio. As expected, a one-sided portfolio should have more execution risk, than a similar two-sided portfolio, because of the additional Delta. Users familiar with Almgren & Chriss models can use to interpret their own optimal execution costs.

The <u>Cost + Risk</u> estimate represents the average shortfall of a trade with <u>no</u> <u>alpha</u> + 1 standard deviation of execution risk. Statistically, traders should expect to beat this value 84% of the time. However this assumes that stock returns are 'normally' distributed – they're not - as the dashed red line in exhibit 15 shows. In reality, the percentage of executions within this limit should be higher – but this is offset by the fact that where this limit is exceeded, the shortfall is likely to be more extreme than expected.

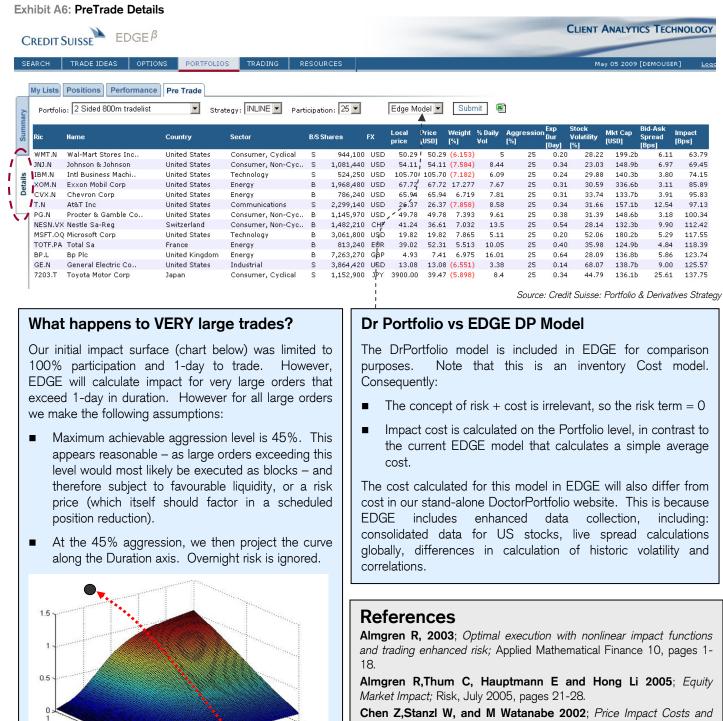
Note: The DP model (included in EDGE - see blue sidebar opposite) is an inventory cost model. As such – it is inconsistent to add a risk term to execution estimates for that model – and this field is not calculated.



Details Screen

The details tab allows you to drill down to stock level details for each trade. This is important with a difficult trade – where more than 5 stocks need special attention – or just to see how specific stocks compare across liquidity, impact or spread factors.

Click-once on any of the headings to sort the list by that field.



the Limit of Arbitrage; Yale School of Management, International Centre for Finance. Lillo F, Farmer J, and R Mantegna 2005; Master curve for price-

Lillo F, Farmer J, and R Mantegna 2005; *Master curve for price-impact function;* Nature, 421, pages 129-130.

21

80

60

Participation [%]

40

20

0 0

0.5

Duration [days]



Portfolio Strategy

USA		
Phil Mackintosh	+1 212 325 5263	phil.mackintosh@credit-suisse.com
Victor Lin	+1 617 556 5658	victor.lin@credit-suisse.com
Glenn DeSouza	+1 212 325 5664	glenn.desouza@credit-suisse.com
Ana Avramovic	+1 212 325 2438	ana.avramovic@credit-suisse.com
Europe		
Stanislas Bourgois	+44 20 7888 0459	stanislas.bourgois@credit-suisse.com
Colin Goldin	+44 20 7888 9637	colin.goldin@credit-suisse.com
Raymond Hing	+44 20 7888 7247	raymond.hing@credit-suisse.com
Laurent Boldrini	+44 20 7888 2041	laurent.boldrini@credit-suisse.com
Marwan Abboud	+44 20 7888 0082	marwan.abboud@credit-suisse.com
Sikandar Samar	+44 20 7888 0604	sikandar.samar@credit-suisse.com
Asia		
Murat Atamer	+852 2101 7133	murat.atamer@credit-suisse.com

Market Commentary Disclaimer

Please follow the attached hyperlink to an important disclosure: http://www.credit-suisse.com/legal_terms/market_commentary_disclaimer.shtml

Structured securities, derivatives and options are complex instruments that are not suitable for every investor, may involve a high degree of risk, and may be appropriate investments only for sophisticated investors who are capable of understanding and assuming the risks involved. Supporting documentation for any claims, comparisons, recommendations, statistics or other technical data will be supplied upon request. Any trade information. Use the following links to read the Options Clearing Corporation's disclosure document: http://www.cboe.com/LearnCenter/pdf/characteristicsandrisks.pdf

Because of the importance of tax considerations to many option transactions, the investor considering options should consult with his/her tax advisor as to how taxes affect the outcome of contemplated options transactions.

This material has been prepared by individual traders or sales personnel of Credit Suisse and its affiliates ('CS') and not by the CS research department. It is not investment research or a research recommendation, as it does not constitute substantive research or analysis. It is provided for informational purposes, is intended for your use only and does not

constitute an invitation or offer to subscribe for or purchase any of the products or services mentioned. The information provided is not intended to provide a sufficient basis on which to make an investment decision. It is intended only to provide observations and views of individual traders or sales personnel, which may be different from, or inconsistent with, the observations and views of CS research department analysts, other CS traders or sales personnel, or the proprietary positions of CS. Observations and views expressed herein may be changed by the trader or sales personnel at any time without notice. Trade report information is preliminary and subject to our formal written confirmation.

CS may, from time to time, participate or invest in transactions with issuers of securities that participate in the markets referred to herein, perform services for or solicit business from such issuers, and/or have a position or effect transactions in the securities or derivatives thereof. The most recent CS research on any company mentioned is at http://www.csfb.com/researchandanalytics.

Backtested, hypothetical or simulated performance results have inherent limitations. Simulated results are achieved by the retroactive application of a backtested model itself designed with the benefit of hindsight. The backtesting of performance differs from the actual account performance because the investment strategy may be adjusted at any time, for any reason and can continue to be changed until desired or better performance results are achieved. Alternative modeling techniques or assumptions might produce significantly different results and prove to be more appropriate. Past hypothetical backtest results are neither an indicator nor a guarantee of future returns. Actual results will vary from the analysis.

Past performance should not be taken as an indication or guarantee of future performance, and no representation or warranty, expressed or implied is made regarding future performance. The information set forth above has been obtained from or based upon sources believed by the trader or sales personnel to be reliable, but each of the trader or sales personnel and CS does not represent or warrant its accuracy or completeness and is not responsible for losses or damages arising out of errors, omissions or changes in market factors. This material does not purport to contain all of the information that an interested party may desire and, in fact, provides only a limited view of a particular market.