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Management of supply chain: an alternative modelling technique for forecasting

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Forecasting is a necessity almost in any operation. However, the tools of forecasting are still primitive in view of the great strides made by research and the increasing abundance of data made possible by automatic identification technologies, such as radio frequency identification (RFID). The relationship of various parameters that may change and impact decisions are so abundant that any credible attempt to drive meaningful associations are in demand to deliver the value from acquired data. This paper proposes some modifications to adapt an advanced forecasting technique (GARCH) with the aim to develop it as a decision support tool applicable to a wide variety of operations including supply chain management (SCM). We have made an attempt to coalesce a few different ideas toward a 'solutions' approach aimed to model volatility and in the process, perhaps, better manage risk. It is possible that industry, governments, corporations, businesses, security organizations, consulting firms and academics with deep knowledge in one or more fields, may spend the next few decades striving to synthesize one or more models of effective *modus operandi* to combine these ideas with other emerging concepts, tools, technologies and standards to collectively better understand, analyse and respond to uncertainty. However, the inclination to reject deep-rooted ideas based on inconclusive results from pilot projects is a detrimental trend and begs to ask the question whether one can aspire to build an elephant using mouse as a model.
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1. Background

Forecasting is an ancient activity and has become more sophisticated in recent years. For a long time, steady steps in a time series data set, such as simple trends or cycles (such as seasonals), were observed and extended into the future. However, now a mixture of time series, econometrics and economic theory models can be employed to produce several forecasts which can then be interpreted jointly or combined in sensible fashions to generate a superior value.

The variable being forecast is a random variable. Originally attention was largely directed towards the mean of this variable; later to the variance, and now to the whole marginal distribution. Pre-testing of the data to find its essential features has become important and that has produced modern techniques such as cointegration.

The horizon over which the forecast is attempted is also important, and longer-run forecasts are now being considered as well as forecasts of 'breaks' in the series.

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The question of evaluation of forecasts has also been greatly developed. Most forecasts are quite easy to evaluate but others, coming from the Global Models (which attempt to model the global economy), are more difficult. Business, commerce, global organizations and governments may find that these models, if explored, may offer valuable guidance for their forecasting activities or their attempts to improve accuracy of forecasts.

Thus, forecasting is a necessity almost in any operation. However, the tools of forecasting (software) in general business use are still primitive in view of the strides made by research. Hence, promoting advances in forecasting to aid predictive analytics is deemed a worthwhile endeavour and is the purpose of this paper. Such tools may further reduce uncertainty and volatility characteristic of global trade. The relationship of various business parameters that may change and impact decisions are so abundant that any credible attempt to drive meaningful associations are in demand by global businesses. This paper proposes some modifications to adapt an already advanced forecasting technique with the aim to develop it as a decision support tool applicable to a wide variety of operations including supply chain management (SCM).

2. Introduction

Total quality management (TQM) gained prominence in the 1970s by claiming to boost quality at a lower cost through proper management and operational design. Lean (manufacturing) was the euphoria in the 1980s following Toyota's exemplary adoption of Just In Time (JIT) processes to enable flexible manufacturing and minimize costs by reducing inventory level. However, it soon became clear that manufacturing costs could not be reduced further by pursuing variations of TQM and JIT simply through classical operations research. Globalization of markets in the 1990s combined with improvements in ICT (information communication technologies) and short product life cycles shifted the focus on SCM that could adapt to demand or reduce costs through improvement in efficiency.

SCM is a set of approaches to efficiently integrate suppliers, manufacturers, distributors, warehouses and retail stores so that merchandise is produced and distributed in the right quantities, to the right locations, at the right time in order to minimize system wide costs while satisfying (customer) service-level requirements (Simchi-Levi *et al*, 2003). Viewed from this perspective, similarities exist between SCM practices and a competitive market economy. A market economy ensures that right mix of goods and services get produced (those that are most wanted by consumers) in the right way (ie least cost) and eventually distributed to the right people (those who are willing to pay the most). Therein lies the attractiveness of a market-based economy, that it gives rise to most efficient allocation of resources. Likewise, SCM, if appropriately designed and executed, may offer efficient business solutions, thereby minimizing costs and improving readiness or competitiveness.

Despite rapid advances in SCM and logistics, inefficiencies still persist and are reflected in related costs. During 2000, supply chain-related costs in the United States alone exceeded \$1 trillion (10% of GDP), which is close to the 2005 GDP of Russia and Canada or the combined GDP of the 22 nations who are members of the oil-rich League of Arab Nations. A mere 10% savings of supply chain costs in the United States is close to the 2005 GDP of Ireland (Datta *et al*, 2004). More than US\$3 trillion have been spent on global logistics in 2004 and this represents almost 5% of the global GDP or more than the GDP of Germany and just less than the GDP of India in 2005. Inefficiencies in the global logistics network estimated at an approximate of US\$600 billion (close to the 2005 GDP of Australia) offers untapped opportunities for organizations to optimize or adapt to improve sustainable profitability. Hence, serious questions have been raised as to how to make decision systems more efficient in order to reduce cost of transaction (Coase, 1960, 1992). This, in turn, requires a thorough understanding of the factors that make design and operation of effective SCM strategy a challenging task due to the volatility of supply and demand.

It is challenging enough to design and operate a supply chain for one facility, in order that costs are minimized and service levels are maintained. The difficulty increases exponentially when the system as a whole is considered and system-wide costs must be minimized, that is, optimizing the interactions between various intermediaries, such as retailer, wholesaler, distributor, manufacturer and supplier of materials. This is mathematically equivalent to finding a global optimal solution as opposed to local optimization, the predominant business practise. Global optimization, involving several stages in the decision-making process, is far more complicated. It is also much broader in scope and encompasses local optimization, but only as a special case.

Some may argue, justifiably, that optimization itself is to be blamed for the inefficiencies in global SCM practices. Perhaps optimization suggests an innate assumption that operations are capable of reaching a steady state or equilibrium, once 'optimal' conditions are determined and executed. Global volatility, even in peaceful or stable political economies, may disprove this assumption. Hence, dynamic or recurrent real-time optimization is required and reflects the fundamental necessity of global supply chains to continuously adapt.

The task of global optimization is rendered difficult by the uncertainty of the business environment. First, businesses need to continually adapt to demand uncertainty and its impact on inventory management. In a market-based economy, production decision is primarily demand driven and must be made *ex ante* (before customer demand is realized). Furthermore, due to lack of information sharing *ex post* (after actual customer demand is realized) between partners, the variability in orders is amplified upstream, along the supply chain. This phenomenon is commonly referred to as the 'Bullwhip Effect' and it is a key driver of inefficiencies associated with SCM. It distorts the demand signals, resulting in costs in the form of excess capacity and inventory, need for increased storage, and transportation cost increases (due to less-than-truckload or LTL scenarios), to name a few (Lee *et al*, 1997).

The Bullwhip Effect and the resulting inefficiencies associated with traditional supply chains may be reduced, in theory, by centralizing information relating to supply and demand (Datta *et al*, 2004). In other words, a 'centralized' supply chain model is one where such information is made available to all participating businesses at various stages of the supply chain or network of partners. Advances in information and communication technologies in the past decade has made it easier to acquire, share, access and analyse data in a manner that is increasingly feasible for 'sense and response' systems. In the context of SCM, the idea is to enable intermediaries in the supply chain process to act as 'infomediaries' or serve as agents for sharing and accessing the real-time data flow through common interfaces, such as web-based services (Datta, 2006, 2007).

Acquisition of or access to data is not equivalent to use of decisionable information that can be extracted from data. Differences in forecasting methodologies applied (to the same data) at different stages of SCM by the participants (process owners) may yield varying types of information that may further obscure the value of data or give rise to increased fluctuations, thus distorting the signals, such as demand (Lee *et al*, 1997). To rein in the Bullwhip Effect, one contribution may stem from a standardized forecasting model, that may be used by the supply chain partners, as an analytical tool to extract value from the data that is accessible to all the partners. Sharing of such an analytical engine by a group of businesses is possible through the use of grid computing (Datta, 2004). Although we have the tools and technologies at our disposable, the sluggish growth of collaborative systems such as CPFR (collaborative planning, forecasting and replenishment) may be indicative of only a mild interest in the benefits of collaborative information processing. It is quite possible that lack of trust between businesses and heightened data security risks may be slowing real-world implementations of valuable strategies such as CPFR.

While a standardized forecasting model applied to near real-time data in a shared or centralized database may try to tame the Bullwhip Effect, it may never be eliminated due to outlier events and inherent or unexplained variability. In SCM, innumerable sources of variability exist, including factors such as demand forecasting, variability in lead time, batch processing or bulk ordering to take advantage of transportation discounts, price variability due to product promotion or discount, to name a few.

Hence, the objective of this paper is to propose the potential use of an advanced statistical modelling technique for the purpose of forecasting (originally proposed by Datta, 2003, 2004). Based on the pioneering work on time series econometrics by Clive W. J. Granger and Robert F. Engle (Engle and Granger, 1987, 1991), this paper proposes a few modifications to the statistical model proposed by Robert F. Engle based on advances in time series econometrics. The modifications were introduced to make the model more amenable for use in decision support systems, such as, SCM. If the proposed modifications are indeed viable, it is expected to explicitly model the interactions between various intermediaries of SCM as well as the time varying (non-constant) variability that manifests, at least in part, as the Bullwhip Effect. For example, our proposed model captures the cross-variable dynamics as reflected in interaction between supply chain nodes or stages (retailers, wholesalers, distributors) using vector auto regression (VAR) methodology which is essentially a model for the means of a vector process. The framework also explicitly models the time varying volatility (perhaps observed, in part, as the Bullwhip effect) by using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) technique (Engle and Kroner, 1995). GARCH is a model for volatility of a single series, whereas multi-variate GARCH (MGARCH) is a model for volatility (variances and covariances) for a vector. Therefore, the proposed model may also be denoted as a VAR-MGARCH model.

While these techniques have been widely used in finance (and economics) in the past few decades (and also earned Engle and Granger the 2003 Nobel Prize in Economics), to our knowledge, they have not been applied or explored as decision support tools by supply chain planners or analysts in the area of SCM.

By using a dynamic model of volatility (defined as standard deviation of variance), a GARCH type model has the added advantage of providing a forecast of volatility in near term. Such a forecast may be useful in calculating value at risk (VaR). However, VaR is estimated with a simplifying assumption, such as (joint) normality. Consequently, ARCH technique has become an indispensable tool in risk assessment and management in the financial sector (Engle and Manganelli, 1999). Globalization of the supply chain has concomitantly increased the risk in the supply chain due to potential for loss of profits from over-capacity (cost of excess inventory) or opportunity lost due to out-of-stock situations. Hence, it is our contention that use of similar methodology in supply chain processes may enable businesses to better manage or even quantify the risk in the process.

VAR-GARCH type models require estimating a large number of parameters and hence cannot be used in practice unless a large sample of data is available. The lack of availability of high volume granular data may explain the scarce interest in applying this modelling technique as a forecasting tool in decision support systems. High volume accurate data is the single most important driver for forecasting accuracy. The recent rejuvenation of the use and adoption of automatic identification technologies (AIT) may partly ameliorate the lack of high volume data. The surge in the use of radio frequency identification (RFID) or ultrawideband (UWB) tags that may be embedded or attached with physical objects, will make it possible to track and locate objects along the entire supply chain, if the systems used by manufacturers, distributors, logistics providers and retailers are able to take advantage of middleware and hardware interoperability (software defined radio or SDR) to monitor, access and share near real-time data from RFID tags or sensors.

Thus, pervasive use of automatic identification may provide high volume object data in near real time with the maturing trend toward ubiquitous computing. Businesses may not have a clear understanding of how to use this data efficiently to extract decisionable and actionable information that offers business value not merely through savings but may actually increase profitability. We propose that businesses explore advanced techniques such as multivariate GARCH that requires high volume of data for estimation but offers the potential to deliver increasingly accurate forecasts along with a measure of VaR. Success in applying similar models to analyse financial market returns is well documented. Global SCM and any operation in need of planning for the future (healthcare, military, emergency) offers interesting applications for VAR-MGARCH techniques.

In the next section, we develop this statistical model for forecasting on a sequential, step-by-step basis, with the idea that independent variables represent operational 'nodes' (for example, the 'stages' or entities in supply chain). Section 4, discusses data requirements for model validation including the significance of automatic identification data. Risk in the global supply chain is qualitatively discussed in Section 5. Concluding thoughts are offered in Section 6 including comments about preliminary results obtained in (only) one study that explored the use of the modification proposed in this paper to simulate improvements in forecasting based on (only) one data source from an ongoing real-world operation.

3. Statistical model: VAR-MGARCH

Forecasting demand is a key tool in managing uncertainty. Forecast accuracy may depend on the understanding and coverage of parameters taken into account and the accuracy of historic data available for each variable that may have an impact on the prediction. In this section, we propose a statistical model that combines classical regression analysis with advanced time series techniques, hopefully to improve accuracy of forecasts.

3.1. CLRM

Classic linear regression models (CLRM) have been around for a century (Studenmund, 2000) and used for a variety of purposes including traditional supply chain planning software. CLRM may be expressed as follows:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{1}$$

where y is the dependent variable of interest to be modelled for forecast (eg sales of a product, say aspirin); t the time period (frequency of observation, for example, $t-1$ may indicate prior week 1, $t-2 \rightarrow$ week 2); β the coefficients to be estimated (based on values of y and x); x the explanatory variable that is used to 'explain' variations in the dependent variable y (for example, low sales of aspirin may be explained by low in-store inventory $\{x\}$ of aspirin) and ε the random (stochastic) error term.

This simple technique can model multiple independent or explanatory variables, that is, multiple x's, since the variation in y, say, sales of aspirin, is dependent on multiple parameters, such as inventory (x_1), price (x_2), expiration date (x_3). The choice of x's (number of explanatory variables) will drive the validity and accuracy of the model. X's may be based on underlying economic principles (theoretical) or business logic (practical underpinnings). However, no matter how many x's are included, there may be an inherent randomness in y that cannot be explained. Thus, the random error term (ε) is included in the equation (admission of the fact that the dependent variable (y) cannot be modelled perfectly). The corresponding mathematical equation is given by Equation (2):

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_K x_{Kt} + \varepsilon_t \tag{2}$$

Objective of CLRM is to estimate the parameters ($\beta_0, \beta_1, \ldots, \beta_K$) of the model based on a *sample* of observations on y and x, assuming that ε is characterized by a normal distribution with mean $= 0$ and variance $= \sigma^2$ for all time periods (t). Normality assumption is needed for hypothesis testing with respect to β's based on sample of data, unless the sample size is large.

$$\varepsilon_t \sim N(0, \sigma^2)$$

Given the multiple sets of $(\beta_0, \beta_1, \ldots, \beta_K)$ may be estimated, the objective of CLRM is to choose that set of $(\beta_0, \beta_1, \ldots, \beta_K)$ which minimizes the sum of squared residuals $(e_1^2, e_2^2, \ldots, e_N^2)$:

$$\sum_{t=1}^{N} e_t^2$$

where $e_t =$ empirical counterpart of ε (and is estimated based on sample data). Intuitively, this amounts to finding a line that best fits the data points by minimizing the sum of squared vertical distances of the actual data points from the fitted line. Thus, residuals are essentially in-sample forecast errors as they measure the difference between actual y and fitted y. This technique is commonly referred to as the principle of ordinary least squares (OLS) and widely used due to its simplicity. The attractiveness of CLRM-based OLS forecasting stems from the fact that we can model cross variable linkages. This feature is especially useful to carry out 'what-if' analysis. For example, what may happen to sales (y, the dependent variable) of aspirin-based painkillers in retail sales if the in-store inventory of non-aspirin painkillers were increased by 10%? Clearly, 'what if' analysis is conditional upon assumptions we make about x's in the model. Therefore, in building this model, the choice of x is a *process* decision based on the model builder's knowledge about an operation or business or industry.

One may wonder if we are playing a 'what if' game or is 10% increase, cited above, a real-world scenario. The retail outlet surely knows what has happened in the past. This segues to the next phase in the development of our statistical model where it is no longer necessary to assume values of the explanatory variable to forecast y (the dependent variable). Instead of inserting arbitrary values for future x's (such as a 10% increase), we start by forecasting the values of x based on its own past data to obtain an unconditional forecast for y. In this stage of model development, the regression technique gets intertwined with time series techniques. By fitting a univariate autoregressive model to x where we use past (lagged) values of x to forecast x, we obtain the following equations (for $x_{1t}, \ldots, x_{Kt}$):

$$\begin{gathered} x_{1t} = \alpha_{10} + \alpha_{11} x_{1t-1} + \alpha_{12} x_{1t-2} + \cdots + \alpha_{1N_{x_{1t}}} x_{1t-N_{x_{1t}}} + u_{x_{1t}} \\ X_{Kt} = \alpha_{k0} + \alpha_{k1} x_{kt-1} + \alpha_{k2} x_{kt-2} + \cdots + \alpha_{kN_{x_{kt}}} x_{kt-N_{x_{1t}}} + u_{x_{kt}} \end{gathered} \tag{3}$$

Rewriting using general notation:

$$y_t = \beta_0 + \sum_{i=1}^{N_{x_{1t}}} \alpha_{1i} x_{1t-i} + \cdots + \sum_{i=1}^{N_{x_{kt}}} \alpha_{ki} x_{kt-i} + \varepsilon_t \tag{4}$$

or

$$y_t = \beta_0 + \sum_{k=1}^{K} \sum_{i=1}^{N_{x_{kt}}} \alpha_{ki} x_{kt-i} + \varepsilon_t \tag{4a}$$

where x_{1t} is the variable x_1 at time t (for example, we used x_1 for inventory, thus x_{1t} is inventory at time t), x_{kt} the variable x_k at time t (up to k number of x's), x_{1t-1} the value of x_1 at time $t-1$ (referred to as the lagged value by one period), N the period up to which the lagged values of x_{1t} will be used in the equation, u the random error term.

Note that β_0 in Equation (4) is a combination of constants from Equations (2) and (3), respectively.

In Equation (3), α_{11}, α_{12} are coefficients of x_{1t-1}, x_{1t-2} and are referred to as lagged weights. An important distinction is that instead of arbitrarily assigning weights, these coefficients are estimated using OLS. The error term in Equation (3) represented by u is analogous to ε in Equation (1). Depending on the number of x's $(x_1, \ldots, x_K)$ that adequately represents the process being modelled in Equation (1), there will be K number of equations as given by (3) that must be estimated to forecast the x's $(x_1, \ldots, x_k)$ which will then be used to obtain an unconditional forecast of y. Thus, to simplify the task, we can estimate all the parameters (α, β) simultaneously by rewriting Equation (1), the basic CLRM equation, as Equation (4) or its shortened version, as in Equation (4a).

Equation 4 is a step toward forecasting the dependent variable (y) with greater accuracy using forecasts of x's based on historical data of x's (lagged values). But, it is also clear that Equation (4) ignores the impact on y of the past values of y itself (lagged values). Consequently, a preferable model will include not only lagged values of x but also lagged values of y, as shown in Equation (5).

$$y_t = \beta_0 + \sum_{j=1}^{N_{yt}} \varphi_j y_{t-j} + \sum_{k=1}^{K} \sum_{i=1}^{N_{x_{kt}}} \alpha_{ki} x_{kt-i} + \varepsilon_t \tag{5}$$

In moving from conditional to unconditional forecasts of y using a time series model, we are increasing the number of parameters to be estimated. In Equation 2, we estimate K parameters $(\beta_1, \ldots, \beta_K)$ excluding (β_0). In Equation 3, we estimate n parameters $(\alpha_1, \ldots, \alpha_N)$ excluding the intercept (α_0) for each of the K number of x's $X_1, \ldots, X_K$). In Equation 5 we estimate j parameters for lagged values of y_{t-j} $(\varphi_1, \ldots, \varphi_j)$ in addition to all the parameters for Equation 4. If we set $K=5$ (five explanatory variables, the x's), $N_x=10$ (number of lagged values to forecast the x's) and $N_y=10$ (number of lagged values of y_t), then, we have increased the number of parameters to be estimated from 5 in Equation (2) to 50 in Equation (4) to 60 in Equation (5 (excluding intercept). To drive precision to the next (logical) step, equation 5 may be expanded further to include the important real-world observations regarding trend, seasonality and other cyclical dynamics. Businesses struggle to uncover 'trends' and once found, they are avidly pursued, often for short term gains but increasingly with less than stellar results due to fickle customer preferences.

3.2. GARCH

Thus far, our discussions have centred on CLRM in conjunction with time series techniques. CLRM is based on a set of assumptions mainly about ε, that, when satisfied, gives rise to desirable properties of the OLS estimates. Needless to emphasize, in the real world, these assumptions are almost always violated. Developments in time series, over the past couple of decades, have addressed the challenges that stem from the violation of some of these classical assumptions leading to inaccurate forecasts.

One of the assumptions often violated in practice relates to homoskedasticity (homo≈equal, skedasticity≈variance or mean squared deviation (σ^2), a measure of volatility) or constant variance for different observations of the error term. Forecast errors are frequently found to be heteroskedastic (unequal or non-constant variance). For example, in multi-stage supply chains, the error associated with manufacturer's forecast of sales of finished goods may have a much larger variance than the error associated with retailer's projections (the assumption being that the proximity of the retailer to the end consumer makes the retailer offer a better or more informed forecast of future sales through improved understanding of end-consumer preferences). The upstream variability reflected in the Bullwhip Effect violates the basic premise of CLRM, the assumption of homoskedasticity. CLRM ignores the real-world heteroskedastic behaviour of the error term ε_t and generates forecasts which may provide a false sense of precision by underestimating the volatility of forecast error.

Homoskedastic and heteroskedastic error term distributions are illustrated in Figure 1. In a homoskedastic distribution, all the observations of the error term can be thought of as being drawn from the same distribution with mean $=0$ and variance$=\sigma^2$ for all time periods (t). A distribution is described as heteroskedastic when the observations of the error term may be thought of as coming from different distributions with differing widths (measure of variance). In supply chains, the variance of orders is usually larger than that of sales. This distortion tends to increase as one move upstream from retailer to manufacturer to supplier. Therefore, the assumption of heteroskedasticity seems more appropriate as a characteristic that may be associated with the Bullwhip Effect.

While variance of error term may change across cross-sectional units at any point in time, it may also change over time. This notion of time varying volatility is frequently observed in financial markets and has been the driving force behind recent advancements in time series techniques. Robert

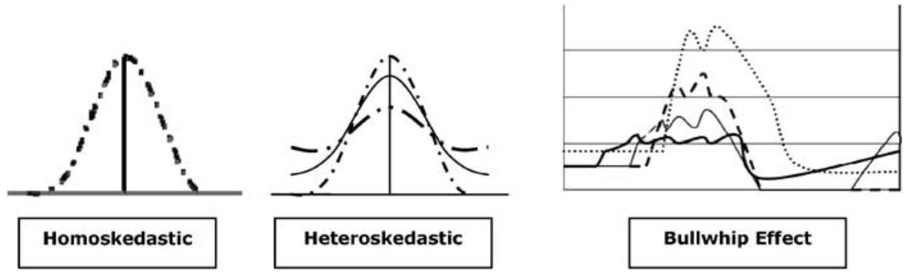

Figure 1 Homoskedasticity, heteroskedasticity and the Bullwhip Effect.

Engle is credited with the observation that not only is volatility non-constant (of financial asset returns), it also tends to appear in bursts or clusters. Instead of considering heteroskedasticity as a problem to be corrected (approach taken by CLRM practitioners in assuming homoskedasticity of error term), Robert Engle seized this opportunity to model this non-constant time-dependent variance (heteroskedasticity) using an autoregressive moving average (ARMA) technique.

ARMA has been in use for several decades and is a combination of AR (autoregression) and MA (moving average) techniques. We have already invoked autoregressive (AR) representation in Equations (4) and (5). AR links the present observation of a variable to its past history, for example:

$$y_t \text{ to } y_{t-1}, y_{t-2}, \ldots, y_{t-p}$$

where p is the order of the autoregressive process AR(p) or the period up to which the historical data will be used (a determination made by using other statistical tools).

Thus, AR is a technique by which a variable can be regressed on its own lagged values. For example, today's sales (y_t) may depend on sales from yesterday (y_{t-1}) and the day before (y_{t-2}). AR(p) is appealing since it links the present to the past. MA expresses observations of a variable in terms of current and lagged values of squared random error terms ε_t, $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ where q is the order of the moving average process MA(q). Combining AR(p) and MA(q), we get ARMA(p, q) where p and q represent the lagging order of AR and MA, respectively.

Robert Engle used the MA technique to model the time varying volatility in a series and proposed the so-called AutoRegressive Conditional Heteroskedasticity model or ARCH. The 'conditional' nature of non-constant variance (heteroskedasticity) refers to forecasting of variance *conditional* upon the information set available up to a time period (t). Using ARCH, the variance of the random error term (ε_t) in Equation (5) can be expanded in terms of current and lagged values of squared $\varepsilon(\varepsilon^2_{t-1}, \varepsilon^2_{t-2}, \ldots, \varepsilon^2_{-q})$ as follows:

$$\sigma^2_t = \theta_0 + \theta_1\varepsilon^2_{t-1} + \theta_2\varepsilon^2_{t-2} + \cdots + \theta_q\varepsilon^2_{t-q} \tag{6}$$

where σ^2_t = variance of $\varepsilon_t[\text{var}(\varepsilon_t)]$.

This MA(q) representation of σ^2_t was later generalized to an ARMA representation of σ^2_t and is referred to as the Generalized AutoRegressive Conditional Heteroskedasticity model or GARCH. The GARCH technique represents a parsimonious model than ARCH, while allowing for an infinite number of past error terms to influence current conditional variance. Hence, GARCH is widely used than ARCH.

GARCH evolved when Tim Bollerslev extended the MA(q) representation of σ^2_t (the ARCH model) to include an AR(p) process, that is, regressing a variable (σ^2_t) on its own (past) lagged values ($\sigma^2_{t-1}, \sigma^2_{t-2}, \ldots, \sigma^2_{t-p}$) as well. Thus, variance of the random error term in a certain period (ε_t) can be modelled to depend not only on squared past errors ($\varepsilon^2_{t-1}, \ldots, \varepsilon^2_{t-q}$) but also on the lagged value of the variance ($\sigma^2_{t-1}, \sigma^2_{t-2}, \ldots, \sigma^2_{t-p}$) as shown in Equation (7) below.

$$y_t = \beta_0 + \sum_{j=1}^{N_{yt}} \varphi_j y_{t-j} + \sum_{k=1}^{K}\sum_{i=1}^{N_{Xkt}} \alpha_{ki} X_{kt-i} + \varepsilon_t$$

$$\sigma^2_t = \theta_0 + \sum_{i=1}^{q} \theta_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \tau_j \sigma^2_{t-j} \tag{7}$$

Thus, GARCH may enable supply chain practitioners to model the volatility in the supply chain, a phenomenon documented by the Bullwhip Effect. How GARCH may help calculate the VaR for various supply chain stages deserves deeper investigation. Future research may reveal a mechanism to quantitatively determine the risk associated with various supply chains. The latter tool, when developed, may be of considerable value in general risk management in the globalized world of international commerce.

3.3. *VAR-GARCH*

In developing the GARCH model, Equation (7) takes into account the lagged values of the dependent variable (sales), the impact of multiple explanatory variables (K number of x's that influence sales such as inventory, price) and their respective lagged values, as well as time-dependent heteroskedasticity of the error term. But, thus far, we have not considered the fact that to predict sales h periods ahead, it is also crucial to model the interaction between the entity level nodes (manufacturer, supplier, distributor in supply chain) which can impact sales.

In any operation, including supply chains, interaction between partners can influence any outcome (profit, service, readiness, response). The strikingly different business 'clock-speed' and dynamics of the supply chains partners is what partly fuels the Bullwhip Effect. Thus, to incorporate the dynamics of interaction between players, it is essential to explicitly model the dynamics between the entities to be a useful real-world model. A combination of vector autoregression technique with GARCH captures this dynamics. Vector autoregression (VAR) is a model for the means of a vector process and was developed over a quarter century ago by Sims (1980). Previously, we discussed AR(p) with respect to Equation (5), which is a univariate model. In contrast, VAR(p) is a n-variate (multivariate) model where we estimate n different equations (for $Y_1, Y_2, Y_3 \ldots Y_n$). In each equation, we regress a variable on p lags of itself as well as p lags of every other variable in the system. Thus, the right-hand side variables are the same for every equation in the system.

The key advantage of VAR lies in its ability to capture cross-variable dynamics (vector process). For example, future sales (prediction) of Michelin brand tyres may not be precisely forecasted by Sears unless the store takes into consideration the events or sales (vector) at the distributor. Thus, there are at least two parties (vectors) in this example (interaction between retail store and distributor). To model this cross variable dynamics of $n = 2$ using VAR(p), let us assume that $p = 1$ (lagged by 1 period). Equation (7) may be extended to the VAR-GARCH type model for two entities with ($n = 2$, $p = 1$, $q = 1$) as shown in Equation (8).

$$
\begin{aligned}
y_{1t} &= \beta_0 + \sum_{k=1}^{K} \sum_{i=1}^{N_{xkt}} \alpha_{ki} X_{kt-i} + \varphi_{11} y_{1t-1} + \varphi_{12} y_{2t-1} + \varepsilon_{1t} \\
y_{2t} &= \beta_0 + \sum_{k=1}^{K} \sum_{i=1}^{N_{xkt}} \alpha_{ki} X_{kt-i} + \varphi_{21} y_{1t-1} + \varphi_{22} y_{2t-1} + \varepsilon_{2t} \\
\sigma_{1t}^2 &= c_{11} + \theta_{11} \varepsilon_{1t-1}^2 + \tau_{11} \sigma_{1t-1}^2 \\
\sigma_{2t}^2 &= c_{22} + \theta_{22} \varepsilon_{2t-1}^2 + \tau_{22} \sigma_{2t-1}^2
\end{aligned}
\tag{8}
$$

In the VAR-GARCH model represented by Equation (8), this dynamics is captured by estimating the coefficient φ_{ij} which refers to changes in y_i with respect to y_j. For example, if y_1 represents Michelin tyre sales at Sears retail store and y_2 represents Michelin tyre sales at the distributor, then the parameter φ_{12} refers to changes in sales at retail store (y_1) with respect to sales at the distributor (y_2). If any one of the two random error terms (ϵ_{1t} and ϵ_{2t}) changes, it will impact both the dependent variables (y_1 and y_2). In terms of Equation (8) above, if ϵ_{1t} changes, it will change y_{1t} and since y_{1t} also appears as one of the explanatory variables for y_{2t} in the equation, the change in any error term impacts both dependent variables in this VAR representation. This cross variable dynamic interaction has thus far been ignored by current modelling practices for forecasting. The VAR component of the proposal in this paper is closer to the real-world scenario and VAR-GARCH may make it possible to quantify such cross-variable dynamics.

3.4. *Multivariate GARCH (MGARCH)*

To move beyond the realm of univariate autoregression to a vector autoregression system, for further precision of forecast, it is necessary to model time varying conditional covariance (measuring the degree of association between any two variables) between ε_1 and ε_2 in addition to time varying conditional variance of the error term. In other words, the error terms associated with the retailer's sales forecast and the distributor's inventory level may be correlated (Granger and Swanson, 1996). This type of multivariate interaction is not explicitly captured by the VAR-GARCH model (Section 3.3), yet in the business world the association between, say, sales forecast and inventory level, is crucial for the overall efficiency and profitability of the supply chain. Thus, the next task is to combine the VAR representation with a multivariate GARCH component. Assuming $p = q = 1$, MGARCH specification can be expressed as follows:

$$
\begin{aligned}
y_{mt} &= \beta_0 + \sum_{k=1}^{K} \sum_{i=1}^{N_{xkt}} \alpha_{ki} X_{kt-1} + \sum_{l=1}^{2} \varphi_{ml} y_{lt-1} + \varepsilon_{mt} \quad \forall m = 1, 2 \\
\sigma_{1,t}^2 &= C_{11} + \theta_{11} \varepsilon_{1t-1}^2 + \tau_{11} \sigma_{1,t-1}^2 \\
\sigma_{12,t} &= C_{12} + \theta_{12} \varepsilon_{1t-1} \varepsilon_{2t-1} + \tau_{12} \sigma_{12,t-1} \\
\sigma_{2,t}^2 &= C_{22} + \theta_{22} \varepsilon_{2t-1}^2 + \tau_{22} \sigma_{2t-1}^2
\end{aligned}
\tag{9}
$$

where $\sigma_{12,t}$ indicates conditional covariance between ε_1 and ε_2 in time period t, based on information set available up to period ($t - 1$).

Thus, the conditional variances and conditional covariances will depend on their respective lagged values, as well as the lagged squared errors and the error cross products. Clearly, estimating such a model may be a formidable task, even in a bi-nodal scenario, for example, a retailer and distributor. If the GARCH system is functional, it may be used to better analyse Impulse Response Function (IRF). At present, IRF values are of limited use because it is difficult to provide confidence intervals for the values. Confidence intervals are necessary for forecasts. GARCH values may provide these confidence intervals. IRF traces the impact of changes ('shock') in error terms on the dependent variable for several periods in the future. Applied to operational planning, IRF may offer insight about 'sense and respond' scenarios. IRF simulation may enable exploration of multi-component 'what if' scenarios by creating challenges and learning (from simulation) how to prepare (readiness) for such challenges (hurricane, fire, flood, earthquake, epidemics, pandemics, military escalations).

3.5. *Is there a link between Bullwhip effect and GARCH processes?*

We have often used 'volatility' to indicate the observation of fluctuation represented by the Bullwhip effect but it is unclear if there is an actual link between Bullwhip Effect and GARCH processes. Simply going 'along' the supply chain, there may not be an use for GARCH but going over 'time' there might be, as explained below.

Consider a supply chain with a sequence of stages or locations: L_0 (origin), L_1 (stage one or first location), L_2 (second), ..., L_f (final stage or end). Goods moving along the chain are associated with a number of delivery times between these locations. Let us denote $T_{j\to k}(t)$ as the time taken to deliver a good from location j to location k, the goods having started at time t at L_0 (origin). The 1st leg of the chain takes time $T_{0,1}(t)$, the 2nd leg $T_{1,2}(t)$ and so forth. These L values are positive random variables, possibly auto correlated, but initially considered as an independent sequence. Note that,

$$T_{0,k}(t) = \sum_{j=0}^{K} T_{j,j+1}(t)$$

is, essentially, a random walk, with an increasing mean and variance. If all the $T_{j,j+1}(t)$ are uncorrelated with mean $m > 0$ and variance v, then $T_{0,k}(t)$ will have mean km and variance kv. As k increases, volatility will increase, which is the Bullwhip Effect (there is no need to use GARCH models to fit this process).

The total time taken for the supply chain $T_{0,f}(t)$ will, as t varies, generate a time series which can be analysed. In the unlikely event that the chain does not change, this will be a stationary series, but it is likely that volatility (Bullwhip Effect) will be experienced by the chain. Thus, an AR-GARCH model may be appropriate.

4. Data

The modelling technique proposed above, may represent an opportunity to apply advanced statistical and econometric tools to improve the quality of predictive analytics in general and supply chain forecasting, in particular. However, validating such a model requires high volume data and involves estimating a large number of parameters. It is possible that advanced organizations, such as the military establishments, may have considered using these techniques but could not substantiate the models due to fewer than necessary reliable data points (degrees of freedom).

However, data 'points' may no longer be the limiting factor if the increasing interest in adoption of AIT is transformed to reality. Widespread adoption of AIT (such as RFID or UWB tags and sensor data) may pave the way for use of real time data to validate a model such as the one proposed in this paper. The innovative convergence of fields as diverse as AIT and time series econometrics may improve decision support systems in domains beyond finance and economics (Datta, 2004).

AIT and progress toward embedding intelligence into physical objects may allow them to communicate with each other (thing-to-thing) as well as with business systems or users (consumers) in near real-time. Hence, businesses may soon be faced with ultra high volume multi-gigabit data streams that may be expressed succinctly only in terms of exabytes per second (1 exabyte $= 10^{18}$ bytes or 10^9 gigabytes). Infrastructure necessary to acquire such data may not offer a satisfactory return on investment (ROI) unless decisionable information derived from this data offers value or profitability. The question of value from high volume data may be considerably enhanced by using data in advanced statistical models (as proposed above) to yield useful analytics.

Availability of near real-time data at the right time may be especially useful for industries where historical data is an agonizing cliché due to short product life cycles, such as mobile phones, digital cameras and laptop computers, which are characteristic of high 'clockspeed' industries (Fine, 1998). For a product with a sales life cycle of 200 days (about 6 months), if we use data from the past 100 days (more than 3 months) in the time series model, it may be difficult to 'change course' and respond or adapt (based on forecasts or predictions from such models). This is where the granularity of high volume AIT data from RFID tags offers the potential to deliver real business value and ROI.

Re-consider the above example but assume the availability of high volume accurate AIT data (from RFID tags on high value products with rapid obsolescence). The data from RFID tags may be modelled with $N = 100$ where data is lagged every hour ($N = 100$ hours instead of $N = 100$ days). However, whether the quality of the information that may be extracted from such data, may change if $N = 100$ is in hours or days, is a business question, not a technology or analytics issue. Consequently, whether high volume data of a certain granularity is sufficient for reliable forecasts will depend on process. If the hourly data is used ($N = 100$), then predictive analysis can be made available within 5 days from launch of a product with 195 days (97.5%) of its sales life cycle still viable, in case it is necessary to re-engineer the product in order to respond to or meet customer preferences. If compared to daily batch data with $N = 100$, analytics may be available after 100 days or with only 50% of the product sales life cycle still viable.

Thus, use of high volume real-time data in these models may make it possible and feasible for sales, marketing, production or distribution to adapt in real-time or at the right-time. Changes can be initiated, based on forecasts, earlier in the (sales) cycle of the product or even at the production stage, by using delayed product differentiation strategies, if products were designed with modular architecture or if the product lifecycle was carefully optimized by balancing the demands of development *versus* fulfillment supply chain parameters.

Regarding estimation technique, the OLS technique, although simple, may not be preferred for use with GARCH. OLS technique proceeds by minimizing sum of squared residuals but residuals, by definition, do not depend on the parameters of the conditional variance equation. Thus, in the presence of GARCH specification, minimizing residual sum of squares is no longer an appropriate objective. Instead, to estimate models from the GARCH family, the maximum likelihood estimation (MLE) is the technique of choice. However, under an assumption of normality, MLE is simply generalized OLS.

MLE works by finding the most likely values of the parameters given the actual data. Multivariate GARCH models are similar to their univariate counterparts and thus MLE technique can be used. However, due to explicit modelling of conditional covariances over time in MGARCH, the number of parameters to be estimated increases exponentially. A few different MGARCH specifications have been proposed, such as the VEC model proposed by Bollerslev *et al* (1988) and the BEKK model proposed by Engle and Kroner (1995). This is an area that warrants deeper exploration keeping in mind increased data availability through use of AIT data acquisition tools.

5. Implications for risk management

Risk in SCM originates from two key areas: supply and demand. At the next level of equal importance are environmental, political, process and security risks. Political and environmental risks may always remain amorphous and refractory to adequate quantification. Security risks are even more volatile but on a higher priority level that demands advanced risk management tools and analysis for targeting operations in global trade.

Too often, risk is viewed as simplistic as merely the product of frequency and consequence. A high-frequency but low-consequence event (currency exchange rates) is viewed as similar to a low-frequency but high-consequence event (sinking of a cargo ship laden with spare parts). In reality, such apparently 'similar risks' may have vastly different effects. Sensational risks grab attention and beg for resource-consuming mitigation while risk managers tend to ignore the smaller risks that create the real friction in the supply chain. With the increasingly complex business environment that is the hallmark of globalization, today's supply chain presents a myriad of specific risks ranging from external sources (such as, terrorist strikes or vulnerability to political instability in developing countries due to global outsourcing) to internal sources (pressure to enhance productivity and reduce costs by eliminating waste, removing duplication through use of single source supplier). If accounted as parameters in traditional optimization equations, the sheer number of factors will exponentially increase the state space and as a result may grind the computation of the optimization algorithms to a pace that may become unacceptable for decision support systems to aid in the management of supply chain adaptability.

The VAR-MGARCH model proposed here may be well suited to take into account the details of the operational nodes (assuming we have data available from each of these nodes/processes). Recurring analysis performed in near real-time (assuming real-time data is available to the analytical engine) may offer results that predicts or detects risks in the operational model (supply chain) far in advance of what is possible at present. The validity of the proposed model as a tool for risk analysis may be tested by simulating a model of a real-world business operation and running the simulation with real-time data (observed or simulated).

Availability of abundant data from various supply chain nodes (supplier, distributor, logistics provider) will reduce risk, if the data is analysed and its impact sufficiently understood to deploy risk mitigation steps, at the right time. Operational transparency at or within supply chain nodes is likely to improve with the increase in object associated data acquisition that may be possible through pervasive adoption of automatic identification (RFID, UWB, GPS, sensors, GE VeriWise System). The use and analysis of this data in a model that captures the end-to-end business network (as well as links to other factors that may impact the function of a specific node) may help to reduce risk. It is in this context that a combination of MGARCH and VAR techniques may offer value hitherto unimaginable.

This model is also relevant to businesses increasingly using 'lean' principles and depends on global outsourcing practices which may compromise the visibility of the supply chain. Transparency of operations within the corporation (internal risk drivers) is as critical as data from business partners in 'lean' and 'global' operations to evaluate external risk drivers. In some cases, outlier events may be even more influential given that uncertainty is far greater than risk and it is very difficult to assign proper weights to distant elephants.

Use of GARCH in supply chain to estimate risk through VaR (value at risk) analysis may also help create a merger of financial and physical supply chains. The financial supply chain, which drives financial settlement, takes over where the physical supply chain ends. Exporters want rapid payment while importers demand accurate data on goods received to better manage inventory and cash-flow to optimize working capital management. Thus, capital efficiency (the traditional domain of the chief financial officer or CFO) depends on data and sharing of information (traditional domain of the chief information or chief technology officer, CIO or CTO) about cross-border movement of goods (customs and excise), transfer of title, risk mitigation and payment. Facilitation of the flow of (decisionable, actionable) information across physical and financial supply chains has a direct impact on working capital.

From a risk management perspective, the supply chain, therefore, appears to evolve as a component of the CFO's responsibility. Adapting the GARCH model to serve as a tool in supply chain risk analysis may offer financial managers a familiar tool that may yield clues to effective supply chain risk mitigation strategies. In general, comprehensive solutions are necessary over the life of a transaction cycle that may integrate cash management, trade settlement, finance, logistics, supply nodes, procurement, demand projections, inventory, human resources, regulatory compliance and management of information across physical and financial supply chain boundaries. Creating one or more models that may work in synergy and integrating such real-world scenarios is a challenge.

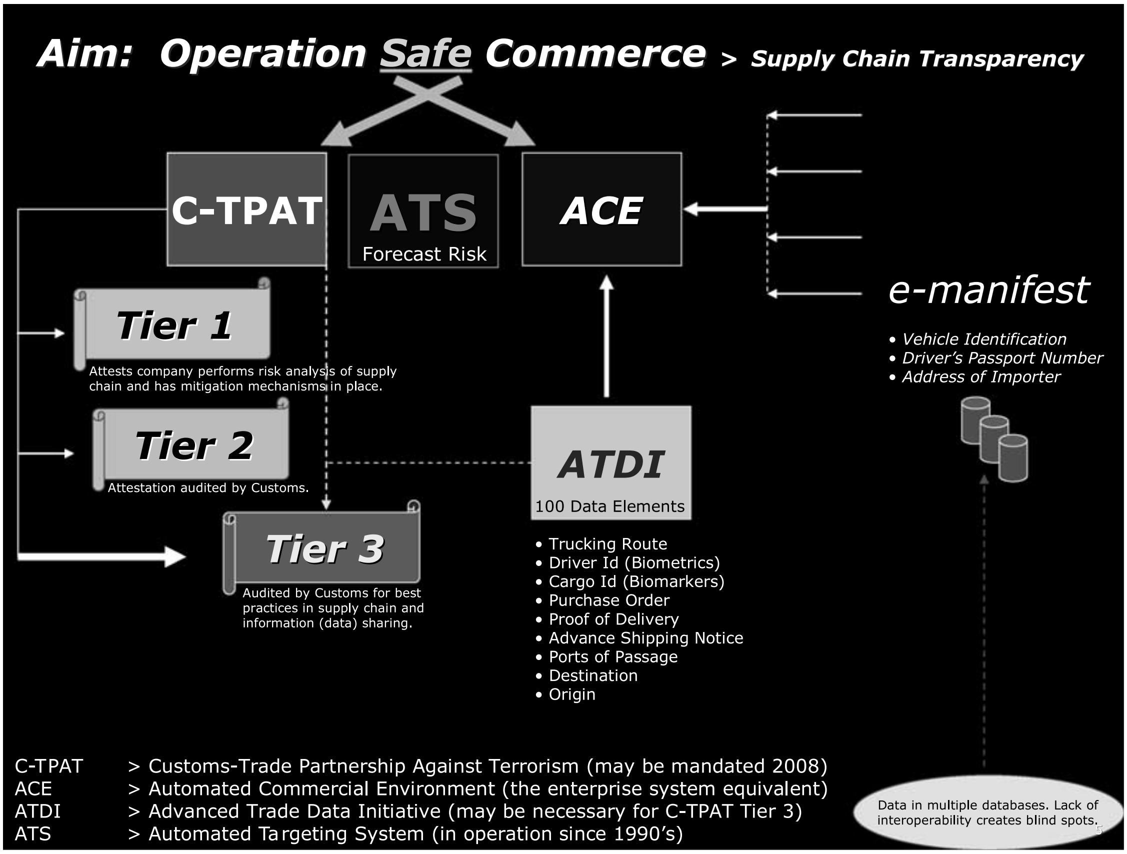

Figure 2 GARCH and Global Risk Management? This illustration outlines some of the pilot projects in progress in the US. There exists a possibility of a mandate by the US in the form of Customs-Trade Partnership Against Terrorism (C-TPAT). To qualify for C-TPAT Tier 3 certification, business must share data through the Advanced Trade Data Initiative (ATDI). Sharing sensitive data will add layers of data security. With data from ATDI, the customs 'enterprise' system or Automated Commercial Environment (ACE) is expected to run analysis to spot anomalies, integrate biometric information (individuals, meat and agricultural products), perform non-obvious relationship analysis (NORA) and forecast risk profile associated with containers or shipments. Armed with this information, customs aims to selectively 'target' cargo for inspections.

However challenging, risk management may soon become a 'household' issue for business and industry. Cost of doing business with and in the US may soon have to figure in the cost necessary to implement transparency in order to mitigate risk. Businesses must share data with US Department of Homeland Security if their goods originate overseas. This model of data sharing may soon be adopted by other countries, determined to counter terrorism. The move toward global supply chain transparency is not a matter of if but a question of when, due to the great uncertainty posed by terrorists that heighten security risks. The lack of analytical tools to make sense of this data may create many more problems before it starts providing solutions. If even a tiny fraction of the 25 000 containers that arrive in US ports each day require inspection, then businesses will face costly delays in receiving customs clearance. In October 2002, a war game that mimicked this delay found that closing US ports for only 12 days created a 60-day container backlog and cost the economy roughly $58 billion (Worthen, 2006).

The proven success of GARCH in finance and the potential to adapt GARCH for business operations may be viewed as one of the promising solutions to offer a synergistic multi-faceted tool for risk-adjusted SCM by acting as a bridge for some of the interdependent issues in global business: finance, supply chain and security risk analysis (Figure 2).

6. Concluding remarks

In this paper, we propose a model for forecasting with potential broad spectrum applications that include SCM. The model is based on advances in time series econometrics. GARCH technique is used to explicitly model the volatility generally associated with supply chains. A VAR framework captures the dynamics of interactions that characterize multi-stage SCM. From a theoretical point of view, such a model is expected to yield an accurate forecast, thereby reducing some of the operational inefficiencies. In addition, businesses and security organizations may benefit from GARCH because it may enable the quantification of VaR associated with a wide variety of processes that require better tools for management of risk.

The proposed model, by its very construction, requires high volume data to estimate a large number of coefficients. Availability of high volume data may not be the limiting factor in view of the renewed interest in AIT that may facilitate acquisition of real-time data from products or objects affixed with RFID tags. Although speculative, it stands to reason that use of a GARCH type model may enhance the ROI from AIT infrastructure by delivering value from acquired data. However, understanding the 'meaning' of the information from data is an area still steeped in quagmire but may soon begin to experience some clarity if the operational processes take advantage of the increasing diffusion of the semantic web and organic growth of ontological frameworks to support intelligent decision systems coupled to agent networks (Datta, 2006).

Rigorous validation of the proposed model with real-world data is the next step. In one isolated experiment, the model proposed in this paper was tested to compare forecasting accuracy. When simulated using real-world data and compared to traditional CLRM type techniques, the GARCH type model provided a forecast that was appreciably closer to the observed or realized value (Don Graham, personal communication). This observation is immature. Several more experiments with rigorous controls must be performed before this result may be even considered to offer 'preliminary' evidence that the GARCH type model proposed in this paper may represent an advanced tool.

In this paper, we have attempted to coalesce a few ideas toward a 'solutions' approach aimed to model volatility in supply chain and in the process, perhaps, better manage risk. It is possible that business, industry, governments, consultants and academics with deep knowledge in one or more fields, may spend the next few decades striving to synthesize one or more models of effective *modus operandi* to combine these ideas with other emerging concepts, tools, technologies and standards to collectively better understand, analyse and respond to uncertainty. However, the inclination to reject deep-rooted ideas based on inconclusive results from pilot projects is a detrimental trend and begs to ask the question whether one can aspire to build an elephant using a mouse as a model.

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