COLLECTIVE OUTSOURCING TO MARKET (COM): A MARKET-BASED FRAMEWORK FOR INFORMATION SUPPLY CHAIN OUTSOURCING

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ABSTRACT

This paper discusses the importance of and solution to separating the information flow and the physical product flow in a supply chain. It is widely observed that information asymmetry exists among supply chain partners. Private information is normally viewed as a source of competitive advantage and is not freely shared among supply chain entities without a proper incentive mechanism. Additionally, the incentive to share information will affect the information quality, which, in turn, will affect the supply chain operation (the physical product flow) through contract design and supply chain coordination. Therefore, effectively sharing quality information among supply chain partners is crucial for improving supply chain efficiency. This paper focuses on the information aspect of the supply chain and proposes a radically new framework called *collective outsourcing to market* (COM) to address many information supply chain design challenges.

Specifically, we consider a supply chain with one manufacturer and multiple downstream retailers. Retailers privately acquire demand forecast information that they do not have incentive to share horizontally with other retailers or vertically with the manufacturer. Our proposed solution is to separate the information flow and physical

product flow in the supply chain and outsource the information-intensive demand forecast task via a market-based mechanism. The specially organized market can be viewed as a cost effective way of acquiring quality information that, at the same time, aligns individual retailers' incentives to credibly share their private information. The market can potentially produce more accurate forecasts by collecting and aggregating dispersed information from a variety of sources.

This paper constructs a theoretical model to illustrate the idea of demand forecast outsourcing as a potential new area of information technology (IT) outsourcing in supply chain management. Our COM framework also demonstrates several benefits of collective intelligence in managing the information supply chain. It has important implications for the alleviation of both the well-known bullwhip effect caused by information distortion and the moral hazard problem in supply chain relational contract design and coordination. In addition, it builds a new foundation for future integrated supply chain risk management and provides an effective trading platform for firms to hedge against systematic risks generated by the changing technological and macroeconomic conditions.

1. INTRODUCTION

Unarguably, demand forecasting plays a critical role in supply chain management. Realizing the importance of accurate forecasting on profitability and efficiency, companies invest aggressively in software and consulting to engage in such costly information acquisition. Pursuing demand forecasting independently is both costly to individual firms and socially inefficient from the supply chain perspective due to the highly correlated demand patterns. Decentralized information acquisition presents contract design challenges in supply chain coordination as well. The contract mechanism has to address the incentives of the firms to truthfully communicate their private demand forecasts. As a result, demand forecasting not only consumes substantial resources from individual firms but yields suboptimal level of supply chain efficiency. Alternative solutions must be sought to improve social welfare. This paper presents a new framework to deal with such information supply chain management challenges. We propose an information market to coordinate the information supply chain where retailers can collectively outsource their respective demand forecasting functions to a specially organized information market. We call this novel framework collective outsourcing to market (COM).

There are a number of important questions that need to be addressed in order to validate such a framework. For example, why is outsourcing demand forecasting, and especially, collective outsourcing needed? Why is outsourcing to market a good idea compared to the traditional approach of outsourcing to a specialized vendor? What are the unique characteristics of COM? How shall the market be designed and organized in order to efficiently aggregate the most accurate demand forecasts? And how can it potentially improve the overall efficiency of information supply chain management? As we answer these questions, we will carefully evaluate other factors as well, such as quality of information, incentive alignment, and contract enforcement. We will also discuss implementation issues.

In the supply chain practice, the idea of outsourcing is not new. In a technological environment characterized by rapid innovation, original equipment manufacturers (OEMs) outsource asset intensive production to contract manufacturers who cut OEMs' costs, free up capital, and improve productivity. As another example, Vendor Managed Inventory (VMI) represents an innovative business process outsourcing (BPO) application in the supply chain through which the supplier takes responsibility for managing the customer's inventory. BPO adopts a transformational business reengineering approach to control relational uncertainty. Vendors (the external service providers) who specialize in specific functional areas can perform the same functions more efficiently at lower cost. Efficiency can be achieved by economies of scale and by tapping the expertise and investments of a provider who focuses solely on that process. Therefore, firms should outsource inefficient areas of operation to realize cost savings and gain expert knowledge. The goal of BPO in supply chains is to effectively reduce both demand-related and process related uncertainties in a dynamic market environment.

However, the current scope of BPO in supply chain management is still limited to manufacturing and logistics. BPO deals are usually related to transfers of physical assets and are yet to be considered as a strategic option in many information-intensive supply chain operations. Barua et al. [2006] have suggested that firms with limited information processing capabilities should implement BPO to collect and deliver quality information for better decision making. This paper discusses the viability of outsourcing the task of demand forecasting in the supply chain. More importantly, we justify the value of collective outsourcing in the supply chain by demonstrating its efficiency gain through the improved capability of quality forecast information.

Our rationale for supply chain demand forecast outsourcing is as follows. First, there are significant correlations across a variety of consumer market demands. Uncertain market demands are usually driven by the underlying uncertainties governed by some macroeconomic factors, such as the adjustment of the interest rate or a nationwide energy shortage. Retailers in the decentralized supply chain can realize significant cost savings in resources and efforts if they can collectively forecast the correlated information. Second, the collective forecasting can be done by a specialized third party who has better ability to analyze data and produce more accurate forecasts. The third party can also conduct its own research to seek outside information if necessary. This would extend the scope of information coordination to other relevant sources, leading to better performance over the traditional supply chain forecasting research (e.g., conducted in-house or through consulting engagements) in which the information coordination is restricted among all the participating partners. Third, information must be shared in a trustworthy way in order to produce an accurate aggregate forecast in the supply chain. Through the outsourcing model, retailers can share decentralized information with the outsourcing specialist, keeping information from being directly released to suppliers and other retailers, and therefore reducing the inefficiency caused by potential strategic interaction among suppliers and retailers. Clearly, economies of scale and specialization in outsourced services can create process efficiency by both lowering cost and increasing quality. Demand forecasting is a process ideally suited for firms to take advantage of the above discussed outsourcing benefits.

Unlike the traditional approach of outsourcing to a specialized vendor, outsourcing to market is a novel idea that has a number of potential benefits. First, market-based interaction will ease contract design and coordination. In traditional outsourcing deals, the firm’s relationship with the outsourcing vendor is specified in a formal service contract. Characteristics such as process complexity, asset specificity, and process maturity, and modularity, are just a few factors that add complication to contract design and negotiation. In addition, the coordination costs increase when uncertainty associated with the transaction increases. Opportunistic costs (due to possible ex post opportunistic behavior of the vendor) could arise in various situations. Loss of resource control and leakage of proprietary knowledge are just two examples of major concerns for firms in making outsourcing decisions. Given a dynamically changing market environment and shortened product life cycles, many strategic alliances end up devolving into temporary market-agreement relationships. As predicted by the transaction cost theory, reduced coordination costs enabled by modern IT infrastructure will increase the use of markets to coordinate economic activity.

Despite the prevalence of the BPO phenomenon, current research in outsourcing theory has yet to quantify the efficiency underlying the information exchange mechanism and the value generation in the supply chain resulting from better quality of information in business decision making. Outsourcing benefits cannot be fully leveraged unless the outsourcing arrangement is carefully planned, including what processes should be outsourced, how to manage the contracts, and what mechanisms can be used to achieve the best possible outcome. As to the mechanism that can be used to manage market-type relationships and encourage cooperation and efficiency in the process of supply chain information outsourcing, the prediction market is one viable concept. Cowles [1933] concluded that expert forecasters could not improve the accuracy of forecasts derived from the actions of a market, and other research findings have generally supported this conclusion. In addition, there have been some recent new applications, including innovations in financial markets, betting on sporting events, and prediction markets. Particularly, a prediction market is an emerging market type that is designed with the sole purpose of forecasting future events. Prediction markets trade specially designed contracts whose payoff is determined according to the outcomes of certain future events. These markets are usually set up as online futures markets with trading rules essentially resembling those of existing stock exchanges such as continuous time double auctions. Prototypes of such markets were used in predicting the most recent presidential election outcome (the Iowa Electronic Market http://www.biz.uiowa.edu/iem) and forecasting movie sales (Hollywood Stock Exchange Market http://www.hsx.com).

In business forecasting, Hewlett-Packard pioneered applications in sales forecasting and now uses internal prediction markets in several business units [Foroohar 2003]. A handful of large companies like IBM, Microsoft, and Ford are eager to join market experiments that utilize the market's predictive power. The impact of prediction markets on science and business is becoming more and more evident. Incentive Markets, a Boston-based consulting company specializing in the pharmaceutical industry, set up an internal futures market for a top-10 drug company that allows employees to bet on the success of products in the pipeline. Net Exchange, the company that developed terror futures, is looking to build predictive markets for investors who want to sell results from a geopolitical risk market to insurance and financial-services firms.

Although initial prediction market experiments have limited scope in application, the trading of many new financial indices is taking place in major clearinghouses. In 2002, Goldman Sachs and Deutsche Bank set up the first markets to trade macroeconomic derivatives – securities whose payoffs are based on future macroeconomic data release such as non-farm payrolls, retail sales, and unemployment claims. Options contracts such as futures can be purchased by traders who believe the future economic data will fall in a certain range. The option prices aggregate individual investors' beliefs and can be used to construct a risk-neutral probability density function to forecast the likelihood of different outcomes. More recently, the Chicago Mercantile Exchange (CME) launched economic derivatives in partnership with Goldman Sachs (http://www.cme.com/trading/prd/auctionmarkets.html), in which new market instruments are designed to measure the "consensus" expectations for leading economic indicators such as U.S. gross domestic product, retail sales, European inflation, and the Institute of Supply Management's purchasing manager index (PMI). Likely outcomes of weekly, monthly, or quarterly future economic data releases are traded in the economic derivative markets. Prices in financial markets play an important role in improving the socially optimal level of information acquisition. This suggests a significant move toward forming market-based consensus forecasts. Guo et al. [2006] have suggested that a macro-index market can facilitate supply chain information coordination and can provide additional risk management capability to supply chain partners.

Clearly, new types of financial markets and financial innovations will emerge to provide superior risk management capabilities. As envisioned by Shiller [1993], innovative financial products, called macro securities, allow people to hedge their stock portfolios, the market value of their houses, and the threat of unemployment or other income fluctuations against aggregate macroeconomic shocks. The CME, mentioned above, houses futures and options as comprehensive financial tools that make it possible to trade U.S. real estate values for investment and risk management purposes.[1] Recently, the Chicago Board of Trade (CBOT) started trading binary options on some macroeconomic indicators in order for customers to hedge their positions. For example, binary options on the Target Fed Funds Rate were designed to provide new trading opportunities for institutional customers to manage or acquire short-term interest rate exposure. It exceeded a 10,000-contract milestone in open interest[2] in less than two months after its introduction. It is viewed as an indicator that customers have embraced the new binary options and use them as a complement to the exchange's Federal Fund futures contracts and an effective way to trade exposure to the Fed's Target Rate (http://www.cbot.com/cbot/pub/cont_detail/0,3206,1036+41413,00.html). As another example, Longitude LLC licenses a Pari-mutuel Derivative Call Auction™ (PDCA™) technology to investment banks and other financial intermediaries to run derivatives auctions and supply risk management products (http://www.longitude.com/html/pdca_technology.html).

As many new prediction subjects become tradable, new types of market mechanisms are proposed to accommodate various business prediction needs. In addition to the popular stock market securities that can be traded publicly in an open market using double auction mechanisms, Chen et al. (2001) have proposed an incentive compatible market mechanism that is suitable for a small group of participants to predict the probability of future events, where each participant's risk attitude is determined to more accurate aggregate their private forecast. More recently, Fang et al.

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[1] Ref: Lex Column: US real estate derivatives, *Financial Times*, May 30, 2006.
[2] Open interest represents the number of trading positions that have not yet been offset and closed at the end of a trading day and is usually considered to reflect the vibrancy of a market.

(2006) introduce a novel betting market to forecast a future value of a specific subject (e.g. the next month's sales). The proposed betting mechanism can elicit both participants' private forecasts and their private evaluation of the forecasting reliabilities. Such a betting mechanism focuses on a selected group of market participants and allows the organizer of the market to have control over the prediction reliability and many other market parameters. Compared to an open market structure, the betting mechanism provides an alternative solution to quality information acquisition. We will discuss their respective advantages and potentials in our supply chain information outsourcing market mechanisms design.

This study seeks to address research gaps in both the outsourcing literature and the supply chain management literature. We propose a radically new idea called *Collective Outsourcing to Market* (COM) to address the effectiveness of collective demand forecast outsourcing in an information supply chain. We illustrate how the demand forecasting of individual supply chain partners can be collectively outsourced to an information market discussed above so that quality information can be acquired in an efficient way to generate economic gains and improve overall system efficiency. Our COM framework also demonstrates a new way of process reengineering in which individual information-related tasks are collectively outsourced without the need to identify, negotiate, and write costly customized contracts with each service provider.

Our major contribution can be briefly summarized as a new supply chain outsourcing initiative enabled by an efficient market-based information revelation and aggregation mechanism. We specifically focus on one important challenge in the information supply chain design – the demand forecasting process – that is traditionally conducted in-house and is viewed as private knowledge and a source of competitive advantage. Our market is designed with the purpose of eliciting and forecasting future macroeconomic events that strongly correlate with the supply chain partners' demand variations. This not only provides supply chain partners with an attractive venue to implicitly outsource their demand forecasting functions, but enables them to purchase insurance to safeguard their operations against profit variances. Specifically, we demonstrate our COM framework using two types of information markets: a double-auction market mechanism as demonstrated in Guo et al. (2006) or a betting market mechanism discussed in Fang et al. (2006), respectively. We show that both mechanisms can separate retailers' decision on information sharing from their operational decision as an equilibrium behavior. Therefore, the overall supply chain efficiency can be improved by using the information market as an information aggregation and supply chain coordination mechanism. The COM framework is viewed as a cost effective way to outsource such an information-intensive task. It also opens new opportunities for hedging other supply chain related risks.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 outlines our COM framework. We then discuss how to construct a macro index market and a betting market for our supply chain collective demand forecast outsourcing problem and compare the applicability of the two markets. We present our main results that quantify the value of collective outsourcing in the information supply chain. In Section 4, we extend our discussion of the COM framework to other emerging business opportunities such as supply chain risk management. We discuss some implementation issues in Section 5 and conclude our paper in Section 6.

2. RELATED LITERATURE

Three streams of literature are particularly relevant to our COM innovation: business process outsourcing, markets as information aggregation mechanisms, and supply chain information sharing.

Transaction cost theory (TCT), first coined by Coase [1937] and later generalized by Williamson [1979], posits that certain economic tasks will be performed by firms while others will be performed by the market, depending on the transaction cost of producing and distributing particular goods or services. Often, inter-organizational relationships are categorized by the kind of contracts involved and the amount of information needing to be processed, generally known as coordination costs. The Internet has greatly reduced communication costs and increased coordination efficiency. Further, it has enabled work to migrate to wherever it can be completed most effectively for the organization. Information technologies make it possible for firms to source business processes from remote locations [Hagel and Singer 1999]. It is further suggested that firms with limited information processing capability need to employ BPO to collect and deliver quality information for decision making [Barua et al. 2006].

The concept of BPO is supported by the view that a firm is a complex system of a large number of business processes [Porter 1996] and can be managed by unbundling the processes into components [Graud et al. 2003]. Cost reduction and quality improvement are cited as the most important motivations for BPO [DiRomualdo and Gurbaxani 1998]. However, productive use of IT usually requires redesign of business processes [Davenport and Short 1990]. As the interaction among business partners becomes more and more information intensive, inter-firm information exchange has become increasingly transformational and collaborative. New business innovation should seek to design efficient information exchange mechanisms that address unique relational needs in the information supply chains.

The efficient market hypothesis (EMH) [Fama 1970] postulates that prices in competitive markets fully reflect all available information. This theory is backed by an increasing amount of empirical evidence [e.g., Spann and Skiera 2003, Wolfers and Zitzewitz 2004]. Previous experimental results seem to suggest that prices perform well as forecasts regardless of the specific characteristics of the prediction market (i.e., the effectiveness of market price as the prediction device is independent of the types of events to be predicted, whether the trading asset is virtual or real money, etc.). The forecasting capability of price appears to be better than existing benchmark methods such as opinion polls [Berg et al. 2005] or surveys from experts [Chen and Plott 2002]. Therefore, the prediction market can be used to elicit particular information of interest with great accuracy. In addition, prediction markets are recommended to serve as decision support tools to aid effective decision making in organizations under various business environments [Berg and Rietz 2003].

Recent research [Gürkaynak and Wolfers 2005] reports initial analysis of the economic derivatives data and finds that market-based measures of expectations are similar to survey-based forecasts, and the market-based measures somewhat more accurately predict financial market responses to surprises in data. Prior successful implementation of various types of prediction markets, as well as the continuous innovation on tradable macro securities, motivate our research on a new type of market acting as a service specialist that serves supply chain partners in predicting, sharing, and managing aggregate supply chain risks.

The theoretical foundation of the EMH concept is based on rational expectation equilibrium (REE) models [Muth 1961]. Generally, this stream of literature, represented by market microstructure models [e.g., Glosten and Milgrom 1985, Kyle 1985], analyzes price informativeness by linking prices to individual trading behaviors. Typically, uninformed market makers set prices according to a predetermined zero profit pricing rule and heterogeneous individual traders sequentially trade in the market based on their available information to maximize expected profits. Information is gradually incorporated into the market price, allowing informed traders to profit from their privileged information. Traders' incentive to reveal their private information is aligned with the market reward mechanism

Among the rich literature on information aggregation mechanisms design, focus has been given to honest reporting while little has been discussed about forecasting incentives. To our knowledge, Osband [1989] is among the first along this research stream to explicitly incorporate agent learning costs into a forecast elicitation model. The analysis suggests that organizations that operate on a "need-to-know" principle can reduce planning cost and control planning efficiency so that forecasting expertise is selected among a handful of capable individuals. Chen et al. [2001, 2004] discuss incentive mechanisms to aggregate decentralized information within a small group to forecast the probability of a future event. Fang et al. [2006] propose a novel betting mechanism to forecast the future value of a business subject when forecasters have heterogeneous ability to acquire signals with different precisions. Such a mechanism can motivate participants to incur certain costs to acquire relevant information. Decentralized information is aggregated efficiently as reliabilities of forecast are utilized to weight each piece of information. With special attention to the cost of information acquisition, they show that the betting market needs to be externally subsidized to insure every trader is appropriately rewarded and hence truthfully reveal their private information.

In the supply chain management literature, Aviv [1998] explores the benefit of sharing forecasts of future demand. As shown by Cachon and Fisher [2000], supply chain total cost is 2.2% lower on average with full information sharing than without using shared information. Although precise demand information may help improve the overall supply chain efficiency, firms are reluctant to share such information, as it may include sensitive sales data. The value of information sharing has also been widely recognized as a solution to the bullwhip effect [Chen et al. 2000]. However, the reluctance of supply chain entities to share their proprietary demand information makes managing information a challenging task [Li 2002]. Shin and Tunca [2006] study the inefficiency of traditional supply chain information coordination. They have proven that retailers will over-invest in their demand forecast when they are competing for market demand in a Cournot fashion and the supplier adopts simple contracts such as one wholesale price, quadratic contracts, or two-part tariff contracts. As an incentive-compatible solution, they propose "market-based" contracting, where each retailer's price depends not only on her own order quantity but also on the order quantities submitted by other retailers. Their contracting scheme aligns the incentives of retailers with those of the supply chain so that the fully coordinated supply chain achieves efficiency both in quantities and investment in demand forecast. However, their proposed solution resembles a VCG [Vickrey 1961, Clarke 1971, Groves 1973] type payment rule that ties the price one pays to the total demand for the product [Bergemann and Välimäki 2002]. Each retailer needs to "conjecture correctly" others' orders in order to decide their optimal quantity. This is a demanding information assumption. The fact that the manufacturer has to write and enforce individual specific contracts contingent on the orders from all participating retailers will complicate the contract management issue.

We provide a simple market-based framework for incentive alignment without adding too much complexity in the contract design for supply chain coordination. There are several major differences in our approach. First, in our macro index market design, we do not explicitly model the cost of demand forecasting but focus on the value of accurate and quality information elicitation and aggregation. Second, they model inefficiency resulting from competition among retailers who have correlated demands. In contrast, we do not have this restriction since, in practice, unwillingness to share information may arise in various strategic considerations that does not necessarily come from direct competition. Third, they assume retailers are symmetric in terms of their cost function for information acquisition. All retailers have an equal effect on the price index. This oversimplification may not correctly represent reality. We argue that a more effective way of coordinating the information supply chain is to separate the information flow from the physical product order flow. Our model is more realistic by allowing asymmetric retailers who have different degrees of correlation with a market macro factor to acquire forecasts at different levels of information precision.

Prior research in the information supply chain literature studies the informational role of an industrial exchange [Whang and Zou 2003]. This work views spot market trading of commodities as an opportunity to share information about demand uncertainty and readjust inventory positions. In contrast, our approach is to introduce a futures market to trade a macroeconomic financial index whose future payoff depends on the realization of a macro factor correlated with the supply chain demand forecast goal. The idea of trading a macro financial index is consistent with observations that a firm's demand has a strong correlation with some financial index [Gaur and Seshadri 2005]. Under our framework, demand uncertainty information can be revealed early and be incorporated into the supply chain partners' contract specification. This paper outlines a model to effectively improve supply chain demand forecast accuracy by collectively outsourcing the task to properly designed markets. It suggests a new business process reengineering approach that sheds some light on managing the information supply chain.

3. THE COLLECTIVE OOUTSOURCING TO MARKET (COM) FRAMEWORK

3.1. THE GENERAL FRAMEWORK

Managing information supply chains presents new information systems design challenges. In a dynamically changing marketplace, both the manufacturer and the retailers need to effectively forecast product demand to reduce their operation overhead. However, individually, each firm has limited capability in its demand forecasting. If each of the retailers chooses an outsourcing vendor to help with the demand prediction, they have to individually negotiate the outsourcing contracts. Not only do they lack the necessary negotiation power, but there is no guarantee that a quality service provider can be found. By collectively outsourcing the demand forecasting function to a third party specialized service vendor, economies of scale can be realized and information quality can be assured.

Figure 1 illustrates our general framework. Consider a supply chain with multiple downstream retailers. The central idea is to separate the information flow from the physical product order flow. The information market acts as the information third party that is capable of eliciting and processing information from a variety of sources. Rather than negotiating a complex outsourcing contract on a one-to-one basis, the information third party designs a standard tradable contract and operates a market in which agents individually determine their respective outsourcing needs. To be specific, the tradable contract is based on a trading asset representing the macro economic perspective to be forecasted. We call the trading asset the retail index. Since individual retailers have private information about the retail index, they can act as informed traders in the market, earning a profit based on their specific information. The contract will reward traders according to the accuracy of their information after future uncertainty is resolved. The information market can collect additional relevant information from other information sources outside the supply chain. The aggregated information revealed in the market can be used to aid in the decision making of both the manufacturer and the retailers.

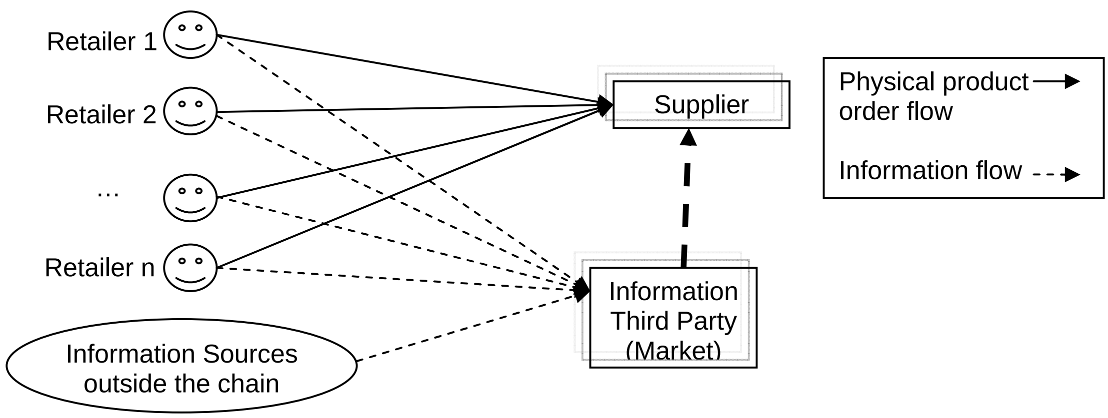

Figure 1: The COM Framework

Our proposed COM framework can address process uncertainty in supply chain management and relational uncertainty in traditional outsourcing contract design. There are several important benefits of outsourcing to the information third party.

The first benefit is its superior ability to process information and produce quality forecasts. The market has the ability to organize and analyze all relevant information into an aggregated market price, representing integrated knowledge for business decisions. The market is an open system that does not restrict the source of information revelation to participating supply chain partners: Relevant information from other sources could be incorporated into the forecast model as well. It can extend the range of information elicitation and hence increase its prediction power. The ability to absorb useful information from sources outside the supply chain is a unique feature of our model that is beyond the scope of traditional supply chain research.

Another important benefit is that the market-based contract is immune to moral hazard problems [Grossman and Hart 1983]. In the supply chain context, moral hazard problems occur when retailers feel economically secured by the manufacturer's contracts, and thus may not take socially conscious actions. For example, a manufacturer may provide retailers with a buy-back contract allowing them to sell back unsold products at a pre-specified salvage value. The retailer may not put much effort into selling products if the promotion cost is higher than the guaranteed salvage value. The market-contingent contract can solve the moral hazard problem since it is written on the retail index, which is highly correlated with the retailers' demand, but retailers still have to bear residual risk of their own uncertain market demand.

In addition, the COM framework can properly align incentives from different parties through its reward mechanism. Since the retailers who make better prediction can expect higher payoffs, the quantitative reward will induce retailers to express their own prediction based on the best of their knowledge. In addition, the open market structure will attract many interested traders, including speculators, liquidity traders, and other experts who believe they have relevant information regarding the forecasted object. No individual is pivotal in influencing the market price. Therefore, our market framework is robust to potential information manipulation by retailers. The market-based outsourcing contract can also benefit retailers by reducing their monitoring costs. The performance of the third party service provider is guaranteed by the effectiveness of the market's informational role. The market is automatically committed to credibly sharing information it has aggregated and processed through the market price formation.

3.2. OUTSOURCING TO AN INDEX MARKET

In this section, we discuss the information market mechanism design using the framework proposed in Guo et al [2006]. Our main purpose is to show the value of the market-based collective forecasting on supply chain information sharing and system efficiency.

To focus on insights and avoid modeling complication, we consider a symmetric supply chain where all the retailers have similar abilities to produce their forecasts. Later we will discuss the possibility of heterogeneous forecasting ability in a betting market mechanism. In our simple supply chain, there are *N* geographically distributed retailers who order a homogeneous product from a manufacturer. Each retailer faces uncertain market demand that can be expressed as a linear function of a macro factor θ representing the systematic risk with an $i.i.d.$ error term ε_i capturing the idiosyncratic risk for retailer i: $D_i = a_i + b_i\theta + \varepsilon_i$, $i = 1, \cdots, N$, where a_i and b_i are known constants that are common knowledge in the supply chain. We assume $\theta \sim N\left(\mu, \frac{1}{\tau}\right)$, $\varepsilon_i \sim N\left(0, \frac{1}{\tau_\varepsilon}\right)$, both normally distributed.

We assume that each retailer can privately derive a forecast for the macro economic factor, $\tilde{\theta}_i = \theta + \delta_i$, where $\delta_i \sim N\left(0, \frac{1}{\tau_\delta}\right)$ is also $i.i.d.$, indicating the forecast error. [3] We also assume that $\tau_\delta > \tau$, implying the forecast is informative because the forecast variance is less than the variance of the prior distribution.

Ideally, if all retailers share their private forecasts truthfully, they will form a common belief on the uncertain macro factor θ, *i.e.*, $\theta \mid \left(\tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_N\right) \sim N\left(\frac{\tau\mu + \tau_\delta \sum_{i=1}^{N} \tilde{\theta}_i}{\tau + N\tau_\delta}, \frac{1}{\tau + N\tau_\delta}\right)$. This aggregated forecast sharing scenario (indexed by *a*) provides us with a full information benchmark solution to evaluate the collective outsourcing efficiency. Another benchmark scenario is a fully decentralized supply chain model without forecast outsourcing (indexed by *d*). In the decentralized model, the information assumption is

[3] In this session, we examine the symmetric case where the retailers have homogenous forecasting abilities by assuming the same precision τ_δ. In later section, we deal with the heterogeneous case with a specially designed betting market mechanism.

that individual retailers can only utilize their own signals to make order decision. The manufacturer, however, has no private signal and can only rely on the common prior belief $\theta \sim N\left(\mu, \frac{1}{\tau}\right)$.

We design a retail index to trade in a marketplace in attempt to predict the true value of θ. Participants can buy or sell contingent contracts at the current market price p based on their respective sources of information. Market trading aggregates the initially locally available forecast information as if participants engage in collaborative forecast projects under the market coordination. This is our COM scenario (indexed by *m*).

Under different information supply chain scenarios, the supply chain partners' decision problems have the same form while conditioning on different information assumptions discussed above. At the second stage, given the manufacturer's wholesale price s^j, *j*=*a*, *d*, *m*, the retailer maximizes her expected profit by choosing order quantity Q_i^j, based on her information set F_i^j:

$$\underset{Q_i^j \geq 0}{Max} \;\; E\left[r \min\left[Q_i^j, D_i\right] - s^j Q_i^j \mid F_i^j\right] \tag{1}$$

where *r* is the unit retail price, $F_i^a = \left\{\left(\tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_N\right)\right\}$, $F_i^d = \left\{\tilde{\theta}_i\right\}$, and $F_i^m = \left\{\tilde{\theta}_i, p\right\}$. p denotes the equilibrium market price.

At the first stage, the manufacturer chooses the wholesale price s^j based on her expected order quantities from the retailers conditional on her own information set Θ^j:

$$\underset{s^j \geq 0}{Max} \;\; (s^j - c)\left[\sum_i E\left[Q_i^j \mid \Theta^j\right]\right] \tag{2}$$

where *c* is the unit production cost, $\Theta^a = \left\{\left(\tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_N\right)\right\}$, $\Theta^d = \varnothing$, and $\Theta^m = \left\{p\right\}$.

3.2.1. Constructing the Index Market

For our purposes, the trading asset in the index market is a futures contract based on a retail index θ, whose payoff depends on the future likely outcome of the macro factor. For simplicity, we assume that one share of the retail index will pay out monetary units

θ.[4] The current price of the futures contract is denoted by p.

While most financial markets operate as a continuous double auction, the market for macroeconomic derivatives is run as a series of call auctions, attempting to maximize liquidity. Similar to those economic derivatives traded in CME, we assume that the index market operates like an open book call futures market [Ref. Fan et al. 2002]. For the sake of liquidity, we also assume that only the risky asset θ is traded in the market. The market opens at a pre-specified time. Trades take place at an equilibrium price reflecting traders' regret-free trading decisions.

The price is determined by the market clearing mechanism that could vary according to different market microstructures. In this paper, we focus on a market structure where the market maker responds to the aggregate net order by taking an opposite position. We assume that the market maker does not have any private information. Thus, to prevent economic loss, the market maker sets the index price as the expected value of the future payoff given the current aggregate net orders in the market.

We assume that there are M risk-neutral informed traders in the market. $M = N + N_0$, where N is the number of retailers and N_0 is the number of outside traders who have relevant information. We also assume that some uninformed traders submit a random, exogenous aggregate net order $\tilde{X} \sim N\left(0, \frac{1}{\tau_X}\right)$. Note that the noise traders' assumption incorporates all the unpredictable elements which may come from market participants' random liquidation demands or irrational behaviors. We don't distinguish among informed traders' forecast abilities. But this simplification will not affect our results.

We provide the definition of REE in the Appendix and characterize the market equilibrium properties as follows. Guo et al. [2006] provide a complete proof of the results. The two properties of market show how an informed trader's trading behavior reveals her private information and how the information is aggregated in the equilibrium market price.

Proposition 1[5]: *There exists a unique linear rational expectation equilibrium (REE) in*

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[4] For notation convenience, we use θ to refer to the macro factor in demand, the trading asset in the market (the retail index representing the macro factor), or its random payoff of the retail index. Readers should be aware of its different interpretation in the specific context.

[5] Conjecture and prove the existence and uniqueness of a linear REE is a standard technique in the

which

1) *An informed trader* i *adopts a linear trading strategy* $\pi_i = \beta_0 + \beta_1\tilde{\theta}_i + \beta_2 p$ *, where* β_0*,* β_1*, and* β_2 *are constants;*

2) *The equilibrium market price* $p = A_0 + A_1\left(\sum_{i=1}^{M}\tilde{\theta}_i + \frac{\tilde{X}}{L}\right)$*, where* A_0 *,* A_1 *, and* L *are constants.*

The two linear equilibrium relations demonstrate how information aggregation can be achieved through the price mechanism. We can see that individual trade decisions are translated into prices since the informed trader's linear trading strategy is self-revealing. At a given market price p, an individual's private signal $\tilde{\theta}_i$ is indirectly transformed into her market trading volume π_i. Accordingly, observing the index price p is equivalent to observing the signal $\left(\sum_{i=1}^{M}\tilde{\theta}_i + \frac{\tilde{X}}{L}\right)$, which is an indicator of the available aggregate market information.

The existence and uniqueness of the linear REE guarantee a one-to-one mapping from the dispersed market signals to the aggregate market price. L , which often represents market liquidity in the REE literature, reflects the precision of the information transformation. The larger the value of L, and/or the less the influence of $\tilde{X}$, the more precise p is as an aggregate indicator of the useful signals.

The aggregate forecasts revealed by the market price can be extremely accurate when the number of informed traders approaches infinity. To quantify this effect, we define *price informativeness* as $PI \equiv \frac{1}{Var[\theta \mid p]}$. That is to say, the less variation of θ conditional on p , the more informative index price p is. We use the reciprocal to capture this relationship in the definition.

Proposition 2: PI *increases in* M *.* $\lim_{M\to\infty} PI = \infty$ *and* $\lim_{M\to\infty} p = \theta$.

Immediately, it implies that price precision increases in the number of informed

financial economics literature. However, due to slightly different informational assumptions in the model setup, no available results can be directly applied. A complete proof of properties 1 and 2 can be obtained by [Guo et al., 2006].

traders. When the number of informed traders approaches infinity, the information revealed in the index market will be accurate enough so that the index price converges to the true value of the macro factor. This property is important, since it guarantees informational efficiency rises as more useful information is impounded in the market price.

As the number of informed traders increases, no individual's order is pivotal to have an effect on the index market price. Since the equilibrium price is determined by the sum of a large number of market participants' signals, one retailer's index market order will only have negligible effects on the information contained in the index price. This implies that retailers do not profit by manipulating their trading orders hoping to mislead the manufacturer in her supply chain pricing decision. Consequently, retailers' index market decisions and physical supply chain order decisions are perfectly separable.

3.2.2. Value of COM on Forecasting

In this section, we show that market-based demand forecast is more accurate than the individual retailer's own forecast. In addition, collective actions of agents who trade in the market produce a more efficient demand forecast that is close to an aggregate forecast, where all supply chain partners truthfully share their own demand forecasts. Finally, it is possible that the overall prediction power of the supply chain partners improves because other sources of useful information can be absorbed and reflected in the equilibrium market prices.

Using the Bayesian rule of update we can derive the respective means ($\mu_i^j, j = a, d, m$) and variances ($\frac{1}{\tau_i^j}, j = a, d, m$) of the forecasted demand distribution under the three supply chain models.

$$\mu_i^a = \frac{\tau}{N\tau_\delta + \tau}\mu + \frac{N\tau_\delta}{N\tau_\delta + \tau}\overline{\theta}\ ,\ \ \mu_i^d = \frac{\tau}{\tau + \tau_\delta}\mu + \frac{\tau_\delta}{\tau + \tau_\delta}\tilde{\theta}_i\ ,$$

$$\mu_i^m = \frac{\tau\mu}{\tau + \tau_\delta + (M-1)^2\tau_v} + \frac{\tau_\delta\tilde{\theta}_i}{\tau + \tau_\delta + (M-1)^2\tau_v} + \frac{(M-1)\tau_v}{\tau + \tau_\delta + (M-1)^2\tau_v}\left(\tilde{\theta}_{-i} + \frac{\tilde{X}}{L}\right),$$

where $\overline{\theta} \equiv \frac{1}{N}\sum_{i=1}^{N}\tilde{\theta}_i$, $\tilde{\theta}_{-i} \equiv \sum_{j\neq i}\tilde{\theta}_j$, $\tau_v = \left(\frac{M-1}{\tau_\delta} + \frac{1}{L^2\tau_X}\right)^{-1}$, and

$$\frac{1}{\tau_i^a}=\frac{b_i^2}{\tau+N\tau_\delta}+\frac{1}{\tau_\varepsilon},\ \frac{1}{\tau_i^d}=\frac{b_i^2}{\tau+\tau_\delta}+\frac{1}{\tau_\varepsilon},\ \frac{1}{\tau_i^m}=\frac{b_i^2}{\tau+\tau_\delta+\left(M-1\right)^2\tau_\nu}+\frac{1}{\tau_\varepsilon}.$$

Since the retailer *i*'s prior demand distribution is a normal distribution with mean $\mu_i^p=a_i+b_i\mu$ and variance $\frac{1}{\tau_i^p}=\frac{b_i^2}{\tau}+\frac{1}{\tau_\varepsilon}$, by simple comparison we obtain the following result.

Proposition 3: *$E_X\mu_i^m=E\mu_i^a=\mu_i^p$, $\tau_i^m\ge\tau_i^p$. Furthermore, there are conditions that, $\tau_i^m>\tau_i^a$.*[6]

Proposition 3 shows that the demand forecast is more accurate under the COM framework in the sense that it yields the same mean but higher precision than the individual forecast. Under some conditions, the COM precision can be higher than the centralized forecast by retailers. This implies the potential better market prediction power.

3.2.3. Value of Information Sharing on the Bullwhip Effect

The bullwhip effect is a well-known informational problem in the supply chain represented by the observed increasing order variances from downstream partners in the supply chain [Lee et al. 1997]. We show that improved demand forecasting reduces the retailer's order variation and thus alleviates the information distortion (e.g., the bullwhip effect) in the supply chain.

It is easy to show that, in our newsvendor-based model, retailer i's optimal order quantity is determined by

$$Q_i^j=a_i+b_i\mu_i^j+\frac{1}{\sqrt{\tau_i^j}}\Phi^{-1}\left(1-\frac{s^j}{r}\right),\ \textit{for}\ \ j=a,d,m,$$

Comparing the order quantities we obtain the following result.

Proposition 4: *$Var\left(Q_i^m\mid p\right)<Var\left(Q_i^d\right)$; $Var\left(Q_i^m\mid p\right)$ decreases in M and $\lim_{M\to\infty}Var\left(Q_i^m\mid p\right)=Var\left(Q_i^a\mid\bar{\theta}\right)=0$.*

Since the index market price is precise enough to forecast the macro uncertainty, retailers can more accurately forecast the macro economy and their own demand when

[6] Please refer to Guo et al. [2006] for a discussion of the specific conditions.

making their order decisions. The index market-based forecast sharing helps reduce order variance from the retailers. The manufacturer can also benefit by making more accurate inferences about the expected aggregate orders from her contracted retailers.

3.2.4. Value of COM on System Efficiency

The outsourced supply chain generates greater total system efficiency than the non-outsourced (decentralized) supply chain. Under certain conditions, COM could produce more accurate forecasts and greater economic gain than the aggregate supply chain solution (the full information benchmark).

The total expected supply chain profit is determined by the sum of all supply chain partners' expected profits.

Define $E\Pi^j = \sum_{i=1}^{N} E\Pi_R^j + E\Pi_M^j = (r-c)E\left[\sum_{i=1}^{N} Q_i^j\right] - rE\sum_{i=1}^{N}\Gamma_{i,j}\left(Q_i^j\right)$, for $j = a,d,m$,

where $\Gamma_{i,j}\left(Q_i^j\right) = \frac{1}{\sqrt{\tau_i^d}}\int_{-\infty}^{-t_j}\Phi(t)dt,\ j = a,d,m$, and $t_j = \Phi^{-1}\left(\frac{s^j}{r}\right)$.

Proposition 5: Under mild regularity conditions, the expected supply chain profit satisfies $E\Pi^a > E\Pi^d$, $E\Pi^m > E\Pi^d$, and $\lim_{M\to\infty} E\Pi^m = \lim_{N\to\infty} E\Pi^a$.

The traditional supply chain literature considers the incentive and coordination issues by viewing the supply chain as a closed system. Our proposed framework demonstrates the value of useful information from other sources to increase overall supply chain efficiency.

3.3. OUTSOURCING TO AN INFORMATION BETTING MARKET

In some supply chain practices, the number of chain partners may not be large. In addition, they may have heterogeneous abilities to predict future uncertainty. That is, the reliability of each retailer's private signals can be different due to their access to potentially different information sources. In this section, we revise the assumption on the information structure in the previous model to address such issue. Specifically, we assume that each retailer *i* obtains a private signal $\tilde{\theta}_i = \theta + \delta_i$, where $\delta_i \sim N\left(0, \tau_i^{-1}\right)$ are independent forecasting errors. τ_i is the precision of each private signals, which is different across the retailers. The larger the τ_i, the less the variance of δ_i and the more precise retailer *i*'s private forecast.

If all the retailers share their signals $\tilde{\theta}_i$ s honestly and the precisions of those signals τ_i s are public information, we shall have that $\theta \mid \left(\left(\tilde{\theta}_i, \tau_i\right), i = 1, 2, \cdots, N\right) \sim N\left(\frac{\tau\mu + \sum_{i=1}^{N} \tau_i \tilde{\theta}_i}{\tau + \sum_{i=1}^{N} \tau_i}, \frac{1}{\tau + \sum_{i=1}^{N} \tau_i}\right)$ following Normal Learning Theorem [DeGroot, 1970]. It is obvious that an efficient aggregation of all the retailers' private forecasts is a weighted average of all the retailers' signals $\tilde{\theta}_i$ and that the weights are proportional to the precision of their signals τ_i. Therefore, in order to get the best aggregation of the signals, not only shall each retailer share their private forecasts $\tilde{\theta}_i$, the reliabilities τ_i s shall also be derived. However, such information is generally unavailable to the market. A mechanism needs to be specifically designed to elicit both $\tilde{\theta}_i$ s and τ_i s.

First we check the validity of relying on a double-auction mechanism described in section 3.2.1 to aggregate dispersed information. In a double-auction mechanism, information is aggregated via the dynamics of price change. As each new bid (ask) order being placed, all the market participants can observe the change, determine what new piece of information the new order implies, and adjust their beliefs accordingly. In order to determine how to update their new beliefs, the traders should have a "correct" conjecture on how the information has been incorporated in the market. This requires that all the traders know the information structure of all the market participants. Theoretically, this is impossible if the precision factors are unobservable. Therefore, a new mechanism shall be implemented to insure the reliability of the forecast.

Recall that in our index market design there is a one-to-one mapping between the trading volume and a trader's signal. If the task of information aggregation is two dimensions (both the signal and the precision), then theoretically we need two market parameters to reveal it. To fulfill this task, we propose to adopt the market mechanism proposed by Fang et al [2006]. The mechanism was designed based on the popular saying "putting your money where your mouth is". Specifically, the information third party can run a betting market to allow all the participants to submit a report r_i on the possible future value of θ and a certain amount of money as a bet of their report, B_i.

The task of the third party is to design a reward function $f(r_i, B_i, \theta)$ paid to each of the participants, which is contingent on the corresponding report and bet, (r_i, B_i). To effectively aggregate the information, the reward function should:

1. induce each participant to report truthfully their private forecast of the future value of θ, that is, $r_i = E\left[\theta \mid \tilde{\theta}_i\right]$;
2. elicit the precision of each bettor's private signal $\tilde{\theta}_i$, that is, $B_i = g(\tau_i)$, where $g(\bullet)$ is monotonic.

One of the candidate reward functions satisfying the above requirement is a quadratic loss function $f(r_i, B_i, \theta) = 2B_i^{\frac{1}{2}}\left(\frac{1}{\tau} - (r_i - \theta)^2\right)$, where the participant maximizes the payoff when the report coincides with the future value of θ.

For each risk-neutral retailer, the overall maximization problem is to decide the report, bet, and their future order quantity so as to maximize their aggregate expected payoff from both the betting market and their local commodity markets. Since all the retailers are risk neutral, the two decisions are independent. Proposition 7 shows the best strategy of each bettor.

Proposition 6: *The bettor i's optimal betting strategy is*

$$\begin{cases} r_i^* = E\left[\theta \mid \tilde{\theta}_i\right] = \dfrac{\tau\mu + \tau_i \tilde{\theta}_i}{\tau + \tau_i} \\ B_i^* = \dfrac{\tau_i^2}{\tau^2 (\tau + \tau_i)^2} \end{cases}.$$

with a positive expected payoff $\dfrac{\tau_i^2}{(\tau + \tau_i)^2}$.

A rational bettor will bet positive amount of money as long as their precision is positive ($\tau_i > 0$). In addition, the bet increases when the signal is more precise (τ_i increases). A bettor with no relevant information ($\tau_i = 0$) will no place a bet. Therefore, the market can effectively aggregate all the relevant information without generating noise traders.

Proposition 7: *Based on bettor i's report and bet (r_i, B_i), the market maker can distill the bettor's private information and precision using the following formulae.*

$$\begin{cases} \tilde{\theta}_i = \dfrac{\tau B_i^{\frac{1}{2}} + r_i - \mu}{\tau B_i^{\frac{1}{2}}} \\ \tau_i = \dfrac{\tau}{1 - \tau B_i^{\frac{1}{2}}} - \tau \end{cases}.$$

This shows that the betting mechanism will reveal both the bettor's signal and its precision. The information can then aggregate all the $\left(\tilde{\theta}_i, \tau_i\right)$s, $i = 1, 2, \cdots, N$ achieving the objective of the two dimensional information aggregation.

3.4. THE ROLE OF THE INFORMATION THIRD PARTY

The proposed COM framework advances the supply chain information coordination by its ability to aggregate dispersed information in different structure and from dispersed sources. A market mechanism is important as an incentive alignment mechanism to reveal the retailer's private forecasts.

Comparing to the index market mechanism, a betting mechanism has merit as to aggregate information when the sources of dispersed information are not evenly distributed. In addition, the information third party can control all the bets and reports not being observable to other bettors. This provides a secure way to incorporating outside information without reviewing the aggregate prediction. The betting market mechanism is especially useful when the forecasting subject is sensitive so the dissemination of information should be restricted within the supply chain. Very often, such sensitive forecasting subject is also hard to attract attention from the public so that it is impractical to trade in an open market environment. Vice versa, a publicly traded index market in section 3.2.1 allows the public to view the information, which is suitable in a forecasting environment where the subject is not sensitive and when the supply chain is large enough to organize such a market in which both retailers and outside experts are interested in participation. In such a case, a public trading index market can be easier to generate public attentions and produce timely results. Everyone who believes they have information can participate and contribute to improve the output of the market.

Our framework emphasizes the separation of the supply chain information flow management and the physical commodity order flow management. To achieve this goal, we suggest that the supply chain partners should collectively outsource their forecasting business to an information third party. The role of the information third party is critical in the success of the supply chain information management. The third party should be trusted by all the chain members to participate and to share information truthfully via the designed reward mechanism. In the case of constructing an open market, the information third party should also be capable of understanding the supply chain information structure, investigating the correlations of the retailers' demands, and identifying the macro factor to forecast. In choosing effective market mechanism, the third party also needs to estimate how the private information is distributed among all the chain partners and whether outside information sources are in need. The information third party is then able to design the appropriate type of prediction market and to deliver the aggregate prediction on time.

4. EXTENSION TO SUPPLY CHAIN RISK MANAGEMENT

In previous sections, we consider risk neutral retailers. Since risk neutral retailers only care about the mean effect of their profit, their strategy is simply to trade the index. In this section, we extend our framework to allow for risk-averse retailers to hedge in the market by providing them with some index-based derivative contracts. We adopt the conventional REE assumption that the market is complete and efficient so that the index-based derivatives can be properly priced, and various index-based derivatives can be traded.

From equation (1) we can see that the retailer has a piecewise-linear payoff function. A kink occurs when the demand equals order quantity. This type of payoff function can be hedged via writing covered call options on the retail index [Hull 1993].

Given the retailer's order quantity Q_i, trading the contingent claim is a Pareto improving strategy because the retailer's expected overall profit is the same in both the index and the commodity markets. However, options can cancel out some uncertainty, thus reducing the profit variance. The contingent claim can be expressed as:

$$\begin{aligned} f_i &= -r\min\left[Q_i, a_i + b_i\theta\right] = r\max\left[-Q_i, -a_i - b_i\theta\right] = -ra_i - rb_i\theta + r\max\left[-Q_i + a_i + b_i\theta, 0\right] \\ &= -ra_i - rb_i\theta + r\left(a_i + b_i\theta - Q_i\right)^+ = -ra_i - rb_i\theta + rb_i\left(\theta - \frac{Q_i - a_i}{b_i}\right)^+ \end{aligned}$$

The contingent claim can be generated by borrowing ra_i shares of riskless bonds and short rb_i shares of the index and long the same shares of a call option with strike price $K_i = \frac{Q_i - a_i}{b_i}$.

Proposition 8: *A risk-averse retailer's Pareto improving index market strategy when ordering Q_i in the supply chain is to borrow ra_i shares of riskless bonds and short rb_i shares of the index θ and long rb_i shares of a call option with strike price $K_i = \frac{Q_i - a_i}{b_i}$.*

This insurance contract links the risk-averse retailer's operational strategy with her financial hedging strategy. We will see that, given other factors fixed, the higher the correlation b_i, the more shares of call option the retailer will purchase, and the lower the strike price required to hedge her inventory position.

In the newsvendor model, risk-averse retailers will order less than the expected value-maximizing quantity [Eeckhoudt et al. 1995] in absence of any risk hedging mechanism. Gaur and Seshadri [2003] show that, under very general conditions, the risk-averse retailer's optimal ordering quantity increases with hedging. Therefore, our constructed index market helps to improve risk-averse retailers' inventory position by allowing for derivatives trading. The COM framework can be further extended to allow for other specially designed contracts to be traded so that hedging other associated economic risks in the supply chain system is possible.

5. IMPLEMENTATION AND DISCUSSION

Our COM framework can be easily implemented in a market setting. Market-based information aggregation and information sharing bring a number of information supply chain design benefits in practical implementation that are impossible to achieve with other traditionally proposed mechanisms in the supply chain literature. In the following, we discuss different aspects of efficiency gains such as avoiding agency problems, providing insurance, and enabling simple and efficient contract design.

5.1. IMPLEMENTATION ISSUES

To increase supply chain operational efficiency, not only should demand forecasts be accurate, but also there should be a proper incentive scheme in place to coordinate activities among all involved entities. As discussed above, the outsourcing market could be operated by a third party vendor that is neutral in the supply chain to avoid the possible gaming and strategic concerns among supply chain partners. However, in a traditional outsourcing arrangement, outsourcing vendors may pursue objectives attractive to them, but that are not necessarily beneficial to the clients. This conflict means businesses need to incur agency costs to monitor the outsourcing vendor's behavior and to create incentive schemes to align the actions of the outsourcing vendor with the interests of the client.

The agency problem arises due to the separation of ownership and control of business firms. The agency problem in its moral-hazard form stems from a basic conflict between insurance and incentives. Without incentive consideration, the theory of optimal insurance suggests that the optimal division of profit between a risk-neutral principal and a risk-averse agent should be that the principal bears all the risk [Borch 1963, Arrow 1970]. However, full insurance conflicts with incentives when the risk-averse agent takes some actions costly to himself and unobservable by the principal. The tradeoff between insurance and incentive objectives generally leaves both parties with suboptimal insurance and suboptimal profits.

While the tradeoff between risk and incentive has been extensively discussed in the agency literature, few effective mechanisms are in place to align incentives or mitigate risks. Finding the optimal incentive scheme when the agent is risk-averse is a complex task, if impossible [Tirole 1998]. Presumably, the outsourcing market and the insurance market could be operated separately by an independent third party. Risk-averse retailers could outsource their demand forecasting task to one market and seek to hedge their operational risk in another. An alternative market organization is that the manufacturer can act as the agent to organize a market for multiple purposes. There are several benefits of this implementation method. First, the market can be used as an efficient information aggregation tool to handle the outsourcing task of demand forecasting. Second, an insurance contract based on the trading asset can be sold to help retailers effectively hedge their operational risk. If the retailers are risk averse, the manufacturer should provide an efficient risk sharing contract to cover most or all of the important retailers' risks, since the manufacturer is the most efficient risk bearer due to economies of scale. Having the manufacturer organizes the market handling both demand forecasting and insurance provision has the benefit of achieving socially efficient outcomes in two aspects. On the one hand, credible information sharing is implemented to increase overall supply chain operational efficiency. On the other hand, if the insurance is provided by the manufacturer instead of an independent underwriter, the scheme will be free from the moral hazard problem and will reduce efficiency loss. This form of implementation requires relatively little monitoring and control.

Finally, efficient implementation requires that supply chain partners' expectations be rational, in the sense that their trading behaviors are based on their assessment and prediction of the future demand that are eventually consistent and correct.

5.2. CONTRACT DESIGN ISSUES

A number of papers discuss supply chain information sharing and supply chain coordination. Research in supply chain contract design has found that supply chain inefficiency arises due to misaligned incentives among competing supply chain partners. As the competition increases, so does the loss of supply chain efficiency. In a recent article, Shin and Tunca [2006] show that common contracting schemes such as wholesale price contracts or two-part tariff contracts combined with downstream competition lead to overinvestment in demand forecasting in the supply chain. They propose an incentive compatible "market-based" contracting scheme to coordinate the supply chain with a linear demand function and downstream competition. A market index is constructed based on all retailers' order quantities and increases with the total order quantity. They propose a quadratic contract form that depends on the index price and combines with quantity discount. The pricing scheme has the same spirit of the VCG mechanism [Vickrey 1961, Clarke 1971, Groves 1973]. Each retailer needs to "conjecture correctly" others' orders to decide their optimal quantity. The actual payment is determined by both the retailer's own order quantity and the other retailers' order quantities.

Although Shin and Tunca [2006] propose an incentive-compatible, regret-free, implementable contracting scheme to coordinate the supply chain, the manufacturer has to write and enforce individual specific contracts contingent on the orders from all participating retailers, which would complicate the contract management issue. More importantly, their market is not a real market.

In this paper, we consider supply chain information sharing without restriction to competing downstream retailers. Therefore, we investigate a more general setting for the informational problem. By separating the information flow from the physical order flow in the supply chain, we are able to find a more efficient way of managing information. Our outsourcing market is a real market that trades futures contracts based on a properly identified macroeconomic factor. Our market is an open system that can attract other traders outside of the supply chain to contribute to the information aggregation. Therefore, it has the potential to generate more accurate forecasts than any individual retailer or what can be obtained through a closed supply chain system.

We provide a simple market-based framework for incentive alignment without adding too much complexity in contract design for the supply chain coordination. We demonstrate that supply chain information coordination can be achieved via collective outsourcing to an information market. With the ability to separate the information flow from the physical product flow, our framework suggests a new way to align incentives in the information supply chain without relying on constructing overly complex and hard-to-implement contracts to achieve the coordination.

6. CONCLUSION

Parallel to the physical supply chain, and fundamentally integral to it, are the information supply chains that help achieve business objectives by enhancing critical business processes. The information supply chain supports business transformation that enables business partners to collectively sense and respond to opportunities and challenges in a networked ecosystem. Success would depend on how well an organization gathers and integrates information in business processes. In this paper, we propose a new market framework to centralize the entire supply chain forecasting task by collectively outsourcing to market and to support information-intensive business process reengineering.

We discuss two radically new market mechanisms that enable new forms of information sharing to deal with different supply chain information management problems. The index market has the potential to extract information outside the supply chain and provides a foundation for hedging other aggregate economic risks in the supply chain. The betting market mechanism is particularly powerful in eliciting private information with different reliabilities. Depending on the characteristics of forecast subjects and the information sharing needs, an information third party can choose the proper mechanisms to fulfill the outsourcing task.

This paper examines the new opportunities in supply chain process innovation. We present an alternative outsourcing model that has some important potential benefits. First, we focus on the economic value derived from a collective knowledge base by considering outsourcing the demand forecast functions that enable the supply chain business process reengineering. Second, collaborative forecasts can be implicitly elicited and effectively coordinated in the marketplace without costly individual contract negotiation and enforcement. Incentives for different supply chain entities to share private information are properly aligned in our market-based framework. In addition, collective outsourcing is more efficient in that it not only pools knowledge from individual firms, but elicits information from other knowledgeable experts who may not necessarily be included in the outsourcing contract to undertake the endeavor. Finally, the market-based framework opens up opportunities for other business innovations. The trading platform has the IT option value that can be fully leveraged to implement other financial innovations such as trading various derivative contracts for supply chain partners to hedge their operational risks.

We contribute to supply chain information systems design by bridging the current research gap between collective outsourcing and the supply chain application. Further work could extend the informational role of markets to its function of hedging firm's operational risk from the supply chain risk management perspective.

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APPENDIX

A. REE IN THE MACRO INDEX MARKET

We assume that each informed trader i obtains a private signal $\tilde{\theta}_i = \theta + \delta_i$, where $\delta_i \sim N\left(0, \frac{1}{\tau_\delta}\right)$, and places an order π_i , for $i = 1,...,M$. There are also some uninformed traders whose aggregate net order is random and exogenously given, i.e., $\tilde{X} \sim N\left(0, \frac{1}{\tau_X}\right)$.[7] The informed trader i takes the price information into account and strategically orders π_i to maximize her expected return from the index market.

$$\underset{\pi_i}{Max} \quad E\left[\left(\theta - p(y)\right)\pi_i \mid \tilde{\theta}_i, p\right] \tag{3}$$

A REE equilibrium is defined by two components. First, a trading strategy π_i, for $i = 1,...,M$, that solves the above maximization problem given pricing function $p(y)$. Second, a pricing function $p(y)$ such that given the trading strategy $\pi_i, i = 1,...,M$, we have

$$p(y) = E\left[\theta \mid y = \sum_{i=1}^{M} \pi_i + \tilde{X}\right] \tag{4}$$

where $y = \sum_{i=1}^{M} \pi_i + \tilde{X}$ is the aggregate demand.

B. PROOFS OF PROPOSITIONS

Proof of Proposition 4:

$$Var\left(Q_i^d\right) = b_i^2 Var\left(\mu_i^d\right) = \frac{b_i^2 \tau_\delta^2}{(\tau + \tau_\delta)^2} Var\left(\tilde{\theta}_i\right) = \frac{b_i^2 \tau_\delta^2}{(\tau + \tau_\delta)^2} \cdot \left(\frac{1}{\tau} + \frac{1}{\tau_\delta}\right) = \frac{b_i^2 \tau_\delta}{\tau(\tau + \tau_\delta)}$$

$$Var\left(Q_i^m \mid p\right) = b_i^2 Var\left(\mu_i^m \mid p\right) = b_i^2 \left[\frac{\tau_\delta - (M-1)\tau_p}{\tau + \tau_\delta + (M-1)^2 \tau_p}\right]^2 \left(\frac{1}{\tau} + \frac{1}{\tau_\delta}\right)$$

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[7] The noise traders' assumption incorporates all the unpredictable elements which may come from agents' random liquidation demands or irrational behaviors. The random supply provided by noise traders is crucial in providing the informed traders with proper incentives to participate in the market. In equilibrium, informed retailers will earn positive expected profits at the expense of the noise traders' expected losses since the market is a zero-sum game.

where $\tau_p \equiv \left(\frac{M}{\tau_\delta}+\frac{1}{L^2\tau_X}\right)^{-1}$, L is a constant market parameter [Ref. Guo et al., 2006].

Comparing equations yields $Var\left(Q_i^d\right) \geq Var\left(Q_i^m \mid p\right)$ with equality holds when *M*=1. So $Var\left(Q_i^d\right) > Var\left(Q_i^m \mid p\right)$ when $M \geq 2$. Proof of the asymptotic property requires substitution of related market parameters. Omit its proof here.

Proof of Proposition 5:

The expected supply chain profits under three supply chain structures are

$$E\Pi^d = (r-c)E\left[\sum_{i=1}^N Q_i^d\right] - r\sum_{i=1}^N \frac{1}{\sqrt{\tau_i^d}}\int_{-\infty}^{-t_d}\Phi(t)dt = (r-c)\left(a+b\mu-\frac{1}{\mathrm{T}^d}t_d\right)-\frac{r}{\mathrm{T}^d}\int_{-\infty}^{-t_d}\Phi(t)dt$$

$$E\Pi^m = E_p\left\{(r-c)E\left[\sum_{i=1}^N Q_i^m \mid p\right] - r\sum_{i=1}^N \frac{1}{\sqrt{\tau_i^m}}\int_{-\infty}^{-t_m}\Phi(t)dt\right\} = (r-c)\left(a+b\mu-\frac{1}{\mathrm{T}^m}Et_m\right)-E_p\left[\frac{r}{\mathrm{T}^m}\int_{-\infty}^{-t_m}\Phi(t)dt\right]$$

$$E\Pi^a = E_{\bar\theta}\left\{(r-c)E\left[\sum_{i=1}^N Q_i^a \mid \bar\theta\right] - r\sum_{i=1}^N \frac{1}{\sqrt{\tau_i^a}}\int_{-\infty}^{-t_a}\Phi(t)dt\right\} = (r-c)\left(a+b\mu-\frac{1}{\mathrm{T}^a}Et_a\right)-E_{\bar\theta}\left[\frac{r}{\mathrm{T}^a}\int_{-\infty}^{-t_a}\Phi(t)dt\right]$$

Therefore,

$$\begin{aligned} E\left[\Pi^m-\Pi^d\right] &= (r-c)\left(\frac{t_d}{\mathrm{T}^d}-\frac{Et_m}{\mathrm{T}^m}\right)+\frac{r}{\mathrm{T}^d}\int_{-\infty}^{-t_d}\Phi(t)dt - E_p\left[\frac{r}{\mathrm{T}^m}\int_{-\infty}^{-t_m}\Phi(t)dt\right] \\ &> (r-c)\left(\frac{t_d}{\mathrm{T}^d}-\frac{Et_m}{\mathrm{T}^m}\right)-E_p\left[\frac{r}{\mathrm{T}^m}\int_{-t_d}^{-t_m}\Phi(t)dt\right] \\ &> (r-c)\left(\frac{t_d}{\mathrm{T}^d}-\frac{Et_m}{\mathrm{T}^m}\right)-\frac{r}{2\mathrm{T}^m}\left(-Et_m+t_d\right) \\ &> \left(\frac{r}{2}-c\right)\left(\frac{t_d}{\mathrm{T}^d}-\frac{Et_m}{\mathrm{T}^m}\right) \end{aligned}$$

where the next to the last inequality follows from the condition $\min\left(s^m, s^d\right) > \frac{r}{2}$ so that $-t_m = \Phi^{-1}\left(1-\frac{s^m}{r}\right) < 0$ and $-t_d = \Phi^{-1}\left(1-\frac{s^d}{r}\right) < 0$. The last inequality requires that $\frac{r}{2} > c$.

Since $\mathrm{T}^d(a+b\mu) = \frac{\Phi(t_d)-x_0}{\phi(t_d)}+t_d$ and $\mathrm{T}^m(a+bp) = \frac{\Phi(t_m)-x_0}{\phi(t_m)}+t_m$, we have

$$\frac{1}{\mathrm{T}^d}g(t_d) = a+b\mu = a+bEp = \frac{1}{\mathrm{T}^m}Eg(t_m) > \frac{1}{\mathrm{T}^m}g(Et_m).$$

The inequality follows by the strict convexity of $g(t)$ when $t \geq 0$. Note that $g(0) \leq 0$. For

$\lambda = \frac{\mathrm{T}^d}{\mathrm{T}^m} < 1$, we have $g(t_d) > \frac{\mathrm{T}^d}{\mathrm{T}^m} g(Et_m) > g\left(\frac{\mathrm{T}^d}{\mathrm{T}^m} Et_m\right)$. So $t_d \geq \frac{\mathrm{T}^d}{\mathrm{T}^m} Et_m$. Therefore, $E[\Pi^m - \Pi^d] > 0$. That is, $E\Pi^m > E\Pi^d$.

$$\begin{aligned}
E\left[\Pi^a - \Pi^d\right] &= (r-c)\left(\frac{t_d}{\mathrm{T}^d} - \frac{Et_a}{\mathrm{T}^a}\right) + \frac{r}{\mathrm{T}^d}\int_{-\infty}^{-t_d} \Phi(t)dt - E_{\bar{\theta}}\left[\frac{r}{\mathrm{T}^a}\int_{-\infty}^{-t_a} \Phi(t)dt\right] \\
&> (r-c)\left(\frac{t_d}{\mathrm{T}^d} - \frac{Et_a}{\mathrm{T}^a}\right) - E_{\bar{\theta}}\left[\frac{r}{\mathrm{T}^a}\int_{-t_d}^{-t_a} \Phi(t)dt\right] \\
&> (r-c)\left(\frac{t_d}{\mathrm{T}^d} - \frac{Et_a}{\mathrm{T}^a}\right) - \frac{r}{2\mathrm{T}^a}\left(-Et_a + t_d\right) \\
&> \left(\tfrac{r}{2} - c\right)\left(\frac{t_d}{\mathrm{T}^d} - \frac{Et_a}{\mathrm{T}^a}\right)
\end{aligned}$$

Since $\mathrm{T}^a\left(a + b\left[\frac{\tau}{N\tau_\delta + \tau}\mu + \frac{N\tau_\delta}{N\tau_\delta + \tau}\bar{\theta}\right]\right) = \frac{\Phi(t_a) - x_0}{\phi(t_a)} + t_a$ and $\mathrm{T}^d(a + b\mu) = \frac{\Phi(t_d) - x_0}{\phi(t_d)} + t_d$, we have $\frac{1}{\mathrm{T}^d} g(t_d) = a + b\mu = \frac{1}{\mathrm{T}^a} Eg(t_a) > \frac{1}{\mathrm{T}^a} g(Et_a)$.

Further, $\tau_i^a > \tau_i^d$ yields $\mathrm{T}^a > \mathrm{T}^d$. For $\lambda = \frac{\mathrm{T}^d}{\mathrm{T}^a} < 1$, we have $g(t_d) > \frac{\mathrm{T}^d}{\mathrm{T}^a} g(Et_a) > g\left(\frac{\mathrm{T}^d}{\mathrm{T}^a} Et_a\right)$. Therefore, $E\Pi^a > E\Pi^d$.

Finally, $\lim_{M\to\infty} E_X \mu_i^m = \lim_{N\to\infty} \mu_i^a$, and $\lim_{M\to\infty} \tau_i^m = \lim_{N\to\infty} \tau_i^a$. The same forecasts yield the same expected supply chain profits.

Proof of Proposition 6:

Given the reward function $f(r_i, B_i, \theta) = 2B_i^{\frac{1}{2}}\left(1 - (r_i - \theta)^2\right)$, an agent maximizes expected payoff by choosing the optimal report and bet, (r_i, B_i):

$$\max_{r_i, B_i} E\left[f(r_i, B_i, \theta) - B_i \mid \left(\tilde{\theta}_i, \tau_i\right)\right]$$

Given the information set $\left(\tilde{\theta}_i, \tau_i\right)$, we have

$$E\left[f\left(r_i,B_i,\theta\right)-B_i \mid \left(\tilde{\theta}_i,\tau_i\right)\right]=2B_i^{\frac{1}{2}}\tfrac{1}{\tau}-B_i-2B_i^{\frac{1}{2}}E\left[\left(r_i-\theta\right)^2 \mid \left(\tilde{\theta}_i,\tau_i\right)\right]$$
$$=2B_i^{\frac{1}{2}}\tfrac{1}{\tau}-B_i-2B_i^{\frac{1}{2}}\left[r_i-E\left[\theta \mid \left(\tilde{\theta}_i,\tau_i\right)\right]\right]^2-2B_i^{\frac{1}{2}}\operatorname{var}\left[\theta \mid \left(\tilde{\theta}_i,\tau_i\right)\right]$$
$$\leq 2B_i^{\frac{1}{2}}\tfrac{1}{\tau}-B_i-2B_i^{\frac{1}{2}}\operatorname{var}\left[\theta \mid \left(\tilde{\theta}_i,\tau_i\right)\right]$$
$$=2B_i^{\frac{1}{2}}\tfrac{1}{\tau}-B_i-2\tfrac{B_i^{\frac{1}{2}}}{\tau+\tau_i}$$

with the maximum obtained when $r_i^*=E\left[\theta \mid \left(\tilde{\theta}_i,\tau_i\right)\right]=\dfrac{\tau\mu+\tau_i\tilde{\theta}_i}{\tau+\tau_i}$. To determine the optimal bet, simply taking first order derivative on $B_i^{\frac{1}{2}}$ of the above equation, we obtain $B_i^{\frac{1}{2}}=\frac{\tau_i}{\tau\left(\tau+\tau_i\right)}$. That is, $B_i^*=\frac{\tau_i^2}{\tau^2\left(\tau+\tau_i\right)^2}$.

Proof of Proposition 7:

Proposition 7 is an immediate result of solving the equations in Proposition 6 for $\left(\tilde{\theta}_i,\tau_i\right)$.